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SURVEY REPORT ON BLOOD VESSEL AND OPTIC DISK SEGMENTATION IN RETINAL IMAGES

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Abstract

The main objective of this project is to detect and segment the blood vessels and optic disk from the digital fundus images. Diabetic Retinopathy is one of the leading causes of visual impairment. It is characterized by the development of abnormal new retinal vessels. This project uses a gray level based features method for segmenting the blood vessels from the optic disk. Fifteen feature parameters associated with shape, position, orientation, brightness, contrast and line density are calculated for each candidate segment. Based on these features each segment is categorized as normal or abnormal using a support vector machine (SVM) classifier. Also this project uses a new template-based methodology for segmenting the OD from digital retinal images. This methodology uses morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation. 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 used.

Index Terms - Blood vessel segmentation, diabetic Retinopathy, moment invariants, optic disk (OD) segmentation, retinal images, SVM Classifier, template-based methodology.

KeyWords

Blood vessel segmentation, diabetic Retinopathy, moment invariants, optic disk (OD) segmentation, retinal images, SVM Classifier, template-basedmethodology.

1 INTRODUCTION

Diabetic Retinopathy (DR) is the leading ophthalmic pathological cause of blindness among people of working age in developed countries. The main cause of DR is abnormal glucose blood level elevation, which damages blood vessel endothelium, thus increasing vessel permeability. The first manifestations of DR are tiny capillary dilations known as microaneurysms. DR progression also cause neovascularization, hemorrhages, macular edema and, in later stages, retinal detachment.

Although DR is not a curable disease, laser photocoagulation can prevent major vision loss if detected in early stages. However, DR patients perceive no symptoms until visual loss develops, usually in the later disease stages, when the treatment is less effective. So, to ensure the treatment, diabetic patients need annual eye - fundus examination. However, this preventive action involves a huge challenge for Health Systems due to the huge number of patients needing ophthalmologic revision, thus preventing many patients from receiving adequate treatment.

The OD plays an important role in developing automated diagnosis expert systems for DR as its segmentation is a key preprocessing component in many algorithms designed to identify other fundus features. On the other hand, to segment the vascular tree, vessel tracking methods need an initial seed vessel points. For this, pixels of vessels within the OD or in its vicinity have been used. OD segmentation is also relevant for automated diagnosis of other ophthalmic pathologies. One of them and maybe the most noteworthy is Glaucoma. It is the second most common cause of blindness worldwide. Glaucoma is identified by recognizing the change in shape, color, or depth that it produces in the OD. Thus, its segmentation and analysis can be used to detect of Glaucoma automatically.

The OD can be distinguished in eye fundus images as a slightly elliptical shape. Its size may vary significantly and different estimations have been made. The OD size varies from one person to another, occupying about one - tenth to one - fifth of the image. In color fundus images, the OD usually appears as a bright yellowish region, although this feature may also experience significant variations. OD segmentation is not an easy matter. Besides the variations in OD shape, size, and color there are some additional complications to take into account. Contrast all around the OD boundary is usually not constant or high enough piecewise due to outgoing vessels that partially obscures portions of the rim producing “shadows”. Another distractor is produced when peripapillary atrophy is present, as this produces bright area just outside the OD rim which distorts its shape. On the other hand, eye movement at the moment of retinography capture may also lead to slightly blurred images, making their automated analysis even more difficult. This problem can be avoided by simply discarding these images and retaking new ones. However, this method is not usually applied as their quality good enough for human visual inspection.

2 REVIEW OF LITERATUE SURVEY

Marc *et al.,* reported about the design and test of an image processing algorithm for the localization of the OD in low – resolution color fundus images. The design relies on the combination of two procedures: 1) a Hausdorff – based template matching technique on edge map, guided by 2) a pyramidal decomposition for large scale object tracking. Three user – specific and computational specifications: 1) robustness to the variable appearance of ODs, 2) detection performance above 90%, and 3) short computation time. An important approach of this is its fast computational time. But the computation time for the Hausdorff stage is dependent upon image content. From this, the observations are, the pyramid based stage has a quite good success when a priori knowledge about the OD position is used but the position found in sometimes quite far from the true OD center and the pyramid approach is of no help in identifying the contour. The Hausdorff – based approach has very good success in finding the OD contour, thus the OD centre, fast and reliability. However, it fails on images where OD contour is very diffuse. The OD is a bright region located either in the left corner or right corner of the fundus images. This assumption is also not always true in practice. Thus the overall image quality, OD appearance may also be good or bad with respect to the sharpness of its contour and its brightness are referred as OD Contour Quality (ODCQ) and OD Brightness Quality (ODBQ).

Sekhar *et al.,* proposed the retinal fundus photograph is widely used in the diagnosis and treatment of various eye diseases such as diabetic retinopathy and glaucoma. The OD is usually the brightest component on the fundus and therefore a cluster of high intensity pixels will identify the OD location. The location of the OD centre was found by calculating the minimum distance between the original retinal image and its projection. Mathematical morphology in image processing is particularly suitable for analyzing shapes in images. This algorithm combining dilation (expands an image object), erosion (shrinks an image object), opening and closing (both for transformations). Processes are used to create mechanisms of edge detection, noise removal and background removal as well as for finding specific shapes in images. The boundary of the OD and its centre are found by applying the Hough Transform to the gradient images. The basic idea behind the Hough Transform is to transform the image into a parameter space that is constructed specifically to describe the desired shape analytically. This method failed to localize the OD due to the ineptness of the shade correction operator and the automatic thresholding. A computer – assisted retinal image analysis system for the localization of OD in color digital fundus images has been presented. The number of edge pixels and the number of radii used is reduced by applying Hough Transform only to the gradient image, since the computational complexity of the Hough Transformation is highly dependent on the number of edge pixels and the number of radii to be matched. This method can be further improved by making a robust shade correction operator and automatic thresholding. And also improves by identifying the OD shape properly by adjusting the Hough Transform to identify both circular and elliptical shapes.

Adam *et al.,* described an automated method to located the optic nerve in images of the ocular fundus. Here using a novel algorithm called fuzzy convergence to determine the origination of the blood vessel network. The optic nerve serves as the conduit for the flow of information from the eye to the brain. The portion of the nerve that is visible in such a view is called the optic disk, referring the two dimensional appearance of the part of the nerve that is visible. This technique could be used for automated patient screening, eye orientation tracking, image sequence registration, and automated measurements for treatment evaluation or diagnosis. If the nerve is completely obscured by hemorrhaging, then it was difficulty in optic nerve detection. This method proposed the optic nerve detection upon finding the convergence of blood vessels. They used multiple vessel segmentation of the same image in order to reinforce the detection of convergent points. To find the vessel network convergence, fuzzy convergence algorithm was used. The success of this method was to detect the optic nerve using fuzzy convergence alone, and in conjunction with using brightness as a salient features. But the problem is identifying a starting point for blood vessel segmentation. They used blood vessel convergence as the primary feature for detection. In fuzzy convergence, the problem of finding the convergence of the vessel network may then be modeled as a line intersection problem. So, model each vessel with a line segment. Two approaches were Least Square solutions to find the point simultaneously minimally distant from all the lines and the data set being fitted is uniformly distributed around the optimal single solution. Subsets of data that do not meet this criterion are termed outliers, and cause wrong solutions. Then the Hough Space methods are transferring data points from an image space to a quantized parameter space. In Illumination equation, the retinal image is uneven. Because of vignetting (result of an improper focusing of light through an optional system) the nerve may appear darker than areas central to the image. To undo the vignetting, the Illumination equation was applied to an image. In hypothesis generation, the regions are sorted by size, and repeatedly partitioned into two sets, the largest value indicates the best partition. From this the nerve detection is considered unsuccessful if either the hypothesized location is wrong or if this method doesn't produced the hypothesis. The results for fuzzy convergence at multiple scales in combination with equalized brightness shows the highest performance overall and complete success on all our healthy retina test cases but the result from the fuzzy convergence at a single scale show that the convergence of the vessel network is a more stable feature of the nerve than the brightness. And also the result from the fuzzy convergence at the multiple scales shows that the persistence of this feature at multiple scales of vessels improves the detection of the nerve. Unlike Least – Squares and Hough Space based solutions, fuzzy convergence used the endpoints of the linear shapes here the blood vessel segments to find the solution.

Juan *et al.,* detailed a deformable – model based approach for robust detection of OD and cup boundaries. It improved and extended the original snake, which is essentially a deforming – only technique in two aspects: 1) knowledge – based clustering and smoothing updated by the combination of both local and global information. This modifications enable the algorithm to became more accurate and robust to blood vessel occlusions, noises, ill – defined edges and fuzzy contour shapes. Optic disk with bright – white region inside called pallor is one of the main components on the fundus image and it is the entrance of the optic nerve and blood vessels to the retina. The method of optic disk boundary detection can be separated into two steps: optic disk localization and disk boundary detection.

Correctly locating the optic disk is the first and essential step for optic disk segmentation. Subsequently the disk centre is estimated and used to initialize the disk boundary. Interference of blood vessels was one of the main difficulties to segment the optic disk reliably and accurately. However, in optic disk boundary detection, pathological changes may arbitrarily deform the shape of OD and also distort the course of blood vessels. Hence deformable templates may not be able to sufficiently encode various shapes of OD from different pathological changes. Cup is the depressed area inside the OD, hence the 3 – D depth is the primary feature of the cup boundary, for which the automated detection is a reliably new task and challenging work in fundus image processing. Currently, the bending of small blood vessels at the cup edge is used as a clue to measure the cup boundary. Nevertheless, this method can only provide several points of cup boundary in the area where there are small blood vessels: for the area without small blood vessels, the cup boundary is not easy to be estimated. A novel approach for automated detection of cup and disk boundaries is based on free – form deformable model technique (snake). This algorithm extends the original snake technique further in two aspects to directly solve the influence of blood vessels without affecting the accuracy. Snake process is modified in two further extensions: 1) after each deformation, the contour points are classified into the edge point cluster or uncertain point cluster by knowledge based unsupervised learning, 2) the contour is updated through variable sample numbers. The updating is self – adjusted using both global and local information so that the balance on contour stability and accuracy can be achieved. The available 3- D OD image and disk boundary are the preconditions to estimate the cup boundary. The automated detection of cup boundary is a challenging task in fundus image processing, the free – form deformation may give uncertain shape if the cup features are not obvious. Therefore, shape model is introduced in the energy function to constrain the deformation to be close to certain predefined shape. This method correctly located the disk boundary while both the GVF snake and modified ASM method failed. This method achieved more successful number of results; and also obtained more accurate boundaries in the successful cases than the other two methods. Clustering operation can perform self – grouping of contour points into uncertain – point cluster and edge – point group based on the knowledge in the extended area of the contour. The estimated C/D ratios based on the detected cup and disk boundaries show good consistency and compatability when compared with the results from HRT (Heidelberg Retina Tomography).

3 CONCLUSION

From the above literatures they proposed either the optic disk or the blood vessels or any other individual part the eye for automated diabetic retinopathy diagnosis. Now I am going to propose a new methodology by considering both optic disk and blood vessel segmentation at the same moment. For this Diego *et al.*, uses a neural network scheme for pixel classification and computes a 7 – D vector composed of gray – level and moment invariants – based feature for pixel representation. Vascular anomalies are one of the DR manifestations, automatic assessment of eye – fundus blood vessels is necessary for automated detection of DR. knowledge on blood vessel location can be used to reduce the number of false positives in microaneurysm and hemorrhage detection. A new methodology is based on pixel classification using a support vector machine (SVM) Classifier. Classification results are thresholded to classify each pixel into two classes: vessel and nonvessel. A postprocessing fills pixel gaps in detected blood vessels and removes falsely – detected isolated vessel pixels. The necessary feature vector is computed from preprocessed retinal images in the neighborhood of the pixel under consideration.

The following process stages may be identified: 1) original fundus image preprocessing for gray – level homogenization and blood vessel enhancement, 2) feature extraction for pixel numerical representation, 3) application of a classifier to label the pixel as vessel or nonvessel, and 4) postprocessing for filling pixel gaps in detected blood vessels and removing falsely – detected isolated vessel pixels. In preprocessing, in order to reduce the imperfections such as lighting variations, poor contrast and noise and generate images more suitable for extracting the pixel features demanded in the classification step: 1) Vessel Central Light Reflex Removal, 2) Background Homogenization, 3) Vessel Enhancement. Next in feature extraction, its aim is pixel characterization by means of a feature vector. The sets of features were: 1) Gray – level based features, and 2) Moment invariants – based features. Each pixel from a fundus images is characterized by a vector in a 7 – D feature space.

In classification step, using SVM classifier classify the homogenized image. Then the final preprocessing step contains two stages are: 1) the first step is aimed at filling pixel gaps in detected blood vessels, and 2) while the second step is aimed at removing falsely detected isolated vessel pixels. The training set robustness shown by our method allows its automated application to images taken under different conditions.

Then in Aquino *et al.*, explains how the OD detection is an important step in developing systems for automated diagnosis of various ophthalmic pathologies. Now I am going to propose a new template – based methodology for segmenting the OD from digital retinal images. And also use a morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation. A location methodology based on voting – type algorithm is proposed for pixel locating within the OD as initial information. The OD processing in eye fundus color images can be grouped into two categories: OD Location (focus on finding an OD pixel – generally representative as its centre), OD Segmentation (estimate the OD boundary). Within this category, a general distinction can be made between template – based methods and deformable or snake methods for extracting the OD boundary as exactly as possible. In OD segmentation process three steps are there: 1) Elimination of Blood Vessels, 2) Obtaining OD Boundary Candidates, and 3) Final OD Boundary Segmentation.

The main conclusions of this work can be summarized as follows: 1) The performance results obtained by the proposed methodology on a huge digital retinal database indicate that simple methods, based on basic image processing techniques, seem to suffice for OD location and segmentation, 2) A Circular modeling for the OD boundary, compared to elliptical and deformable models, offer good compromise between success rate, quality and efficiency, as shown by comparing its segmented area to experts free drawn areas, 3) In BV segmentation its pixel classification procedure is based on computing only seven features for each pixel, thus needing shorter computational time, and 4) The demonstrated effectiveness and robustness, together with its simplicity and fast implementation, make this proposed automated blood vessel segmentation method a suitable tool for being integrated into a complete prescreening system for early DR detection.

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