BLOOD LINEAR SEGMENTATION USING NAVIES BAYES CLASSIFIER

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ABSTRACT

An uncomplicated, hasty and efficient fusion segmentation method is accessible for extracting vessel structures in retinal fundus images. Basically, this fusion move towards combines globular and naive Bayes classifiers to haul out blood vessels in retinal fundus metaphors. The circular method samples pixels along the enlarging circles entered at the contemporary pixel and classifies the present pixel as vessel or non-vessel. A purging technique is then engaged to eliminate the non-vessel wreckage from the processed image. The naive Bayes method as a organize method uses an incredibly tiny set of characteristics to section retinal vessels in retinal images. The designed fusion method exploits the circular and Bayesian segmentation results together to achieve the best performance. The proposed methods segment a retinal image within 1 s and achieve about 95% accuracy. The results also indicate that the proposed hybrid method is one of the simplest and efficient segmentation methods among the unsupervised and supervised methods in the literature.

I.INTRODUCTION

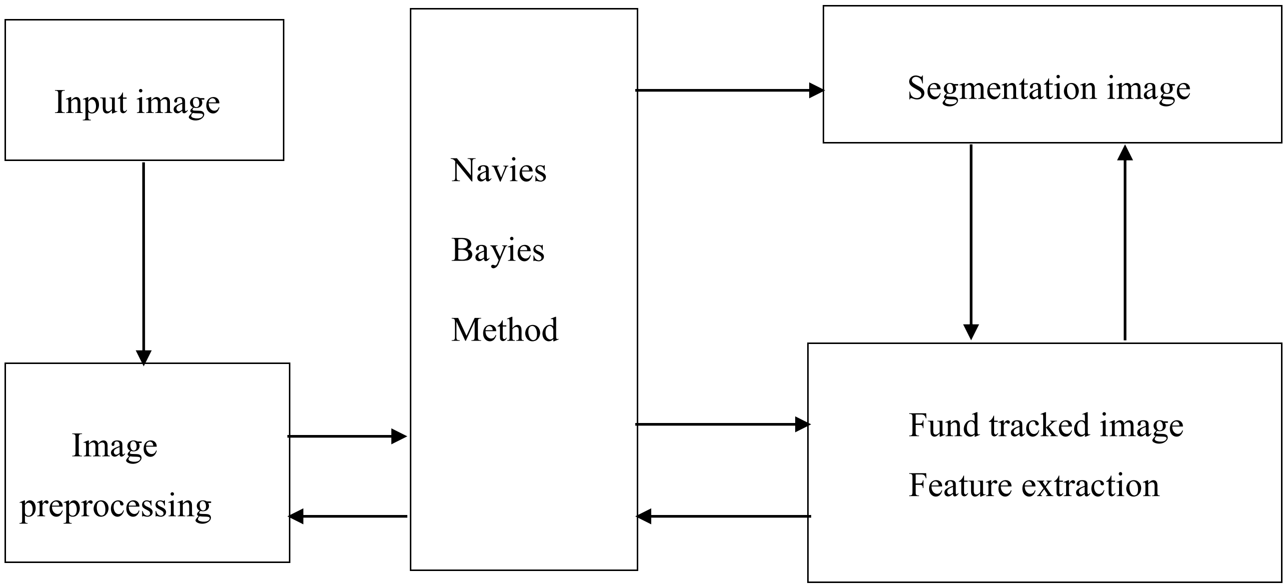
Retina is the tissue lining the interior surface of the eye which contains the ligh sensitive cells (photoreceptors). Photoreceptors convert light into neural signals that are carried to the brain through the optic nerves. In order to record the condition of the retina, an image of the retina (fundus image) can be obtained. A fundus camera system (retinal microscope) is usually used for capturing retinal images. Retinal image contains essential diagnostic information which assists in determining whether the retina is healthy or unhealthy.Retinal images have been widely used for diagnosing vascular and non-vascular pathology in medical society. Retinal images provide information on the changes in retinal vascular structure, which are common in diseases such as diabetes, occlusion, glaucoma, hypertension, cardiovascular disease and stroke. These diseases usually change reflectivity, tortuosity, and patterns of blood vessels. For example, hypertension changes the branching angle or tortuosity of vessels and diabetic retinopathy can lead to revascularization i.e., development of new blood vessels. If left untreated, these medical conditions can cause sight degradation or even blindness. The early exposure of these changes is important for taking preventive measure and hence, the major vision loss can be prevented.Automatic segmentation of retinal blood vessels from retinal images would be a powerful tool for medical diagnostics. For this purpose, the segmentation method used should be as accurate and reliable as possible. The main aim of segmentation is to differentiate an object of interest and the background from an image.

EXISTING SYSTEM :

Automatic segmentation and measurement of vessel structures are main research areas in retinal image analysis, which are extremely important in detecting and monitoring eye illnesses and taking early precautions for their effective treatment. Automatic systems are required to perform labor and computationally intensive tasks including extraction, measurement, visualization, and evaluation of retinal blood vessels. A standard grading system is used in manual assessment of retinal images. Manual assessment also requires ophthalmologists or professionally trained graders to analyze large numbers of retinal fundus images. In manual evaluation, segmentation and measurement accuracy also varies depending on the quality of the retinal images and graders' ability and experience.

PROPOSED SYSTEM :

The proposed retinal vessel segmentation method takes advantages of the rule-based unsupervised and supervised methods. The circular segmentation method uses neighboring pixels around the current pixel that is being processed to extract spatial consistency available in the image. For circular segmentation, color retinal images are transformed into grayscale images and then inverse images of the grayscale images are generated. Then a simple approach with circular sampling is employed in segmentation of the retinal vessels. On the other hand, the naive Bayes method as a supervised technique exploits a very small set of features to segment retinal vessels in retinal images. Finally, the proposed hybrid method combines the results generated by circular and Bayesian segmentation to achieve a better segmentation performance.



MODULE DISCRIPTION

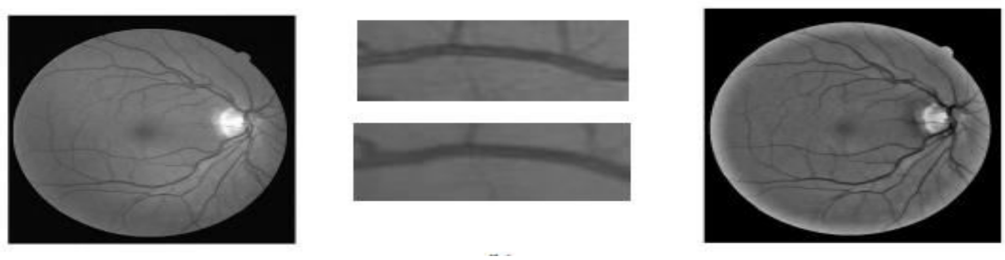
1. Preprocessing

The retinal image usually has imperfections like poor contrast and noise, which need to be reduced or eliminated before extracting pixels' features for classification. So preprocessing is necessary step to be followed, which includes different sub steps. In general, retinal blood vessels have lower reflectance and appear darker than other structures in a retinal image. By applying morphological opening to the green channel of image, the bright central lines can be removed from the blood vessels.

Gaussian kernel of dimension $m \times m = 9 \times 9$, $mean = 0$, and $standard\ deviation = 1.8$, which further reduces the noise and is denoted by $I\ g$. Secondly, $I\ g$ is passed through 69×69 mean filter, which blurs the retinal image and yields the background image, Ib. The difference between $I\ g$ and $I\ b$ is calculated for every pixel, and the result is used for generating shade corrected image:

$$D(x,y) = I_g(x,y) - I_b(x,y)$$

Lastly, the shade corrected image ($I\ sc$) is generated by transforming linear intensity values into the possible gray levels (8-bit image: 0-255) values



(a) (b) (c)

figure: (a) Green channel of original retinal image (b) Green channel image(c) Shade corrected image

This is minimized by forming homogenized image *I h*, using gray-level transformation function:

$$g_{\text{Output}} = \begin{cases} 0, & if\ g < 0 \\ 255, & if\ g > 255 \\ g, & otherwise \end{cases}$$

Where, $$g = g_{\text{Input}} + 128 - g_{\text{Input\_max}}$$

Here, gInput and gOutput are the gray level variables of input (I sc) and output (I h) respectively and g Input max is the gray level value of input (I sc), which has highest number of pixels of the homogenized

2. Gray level and moment invariant based features

The term gray level refers to the intensity of a particular pixel in the image. In segmentation of image using supervised method, the sequence of gray levels of pixels neighbours can be used as a feature vector. A feature vector is a vector that contains information describing an object's important characteristics. Image moments and moment invariants could help in object recognition and its analysis.

3. Feature extraction

Image features are distinctive attributes or aspects of image, which is important in image processing. The features which are extracted from the image are useful in classifying and recognition of image. And the features extracted during this phase helps in classifying pixels whether it belongs to vessel or not. Two different kind of features; gray level based features and moment invariant based features are extracted.

4. Supervised method

Pattern recognition is the process of classifying input data into objects or classes by the recognition and representation of patterns it contains and their relationships. It includes measurement of the object to identify attributes, extraction of features for the defining attributes, and comparison with known patterns to determine the class-memberships of objects; based on which classification is done. Pattern recognition is used in countless applications, such as computer aided design (CAD), in medical science, speech recognition, optical character recognition (OCR), finger print and face detection, and retinal blood vessel segmentation.

5. Bayesian segmentation method

The naive Bayes method as a supervised approach is introduced for segmentation of the retinal vessels. The naive Bayes classifier, introduced in this paper, uses a very small set of features to segment the retinal vessels efficiently. These features are colors ($R; G;B$) and intensity values; color ratios of pixels such as $G=(R + G)$,$B=(R + B)$, and $B=(G + B)$; and Rt and Rs values. The proposed Bayesian classification approach uses only nine features to segment retinal vessels efficiently. The mean, standard deviation (SD), and P-values of the features used in this application for vessel and nonvessel areas. In segmentation, the classifier used to extract vessel structures in retinal fundus images. In the application, an independent probability distribution is determined for each of these features and then pixels are classified by employing the equation. Here, the Bayesian segmentation method is applied in two stages, which are training and classification. After the training, the classifier is applied to each pixel of the input image to generate the Bayesian segmentation result ($IBS(x; y)$) .

$$\text{Classify } (f_1, \ldots, f_n) = \max_k \left\{ p(C_k) \prod_{i=1}^{n} p(f_i|C_k) \right\},$$

Where C, n, k, f, and i stand for classes, number of features, class variables, features, and feature indices, respectively. P (fijCk) and p(Ck) represent the independent probability distributions and class priority, respectively.

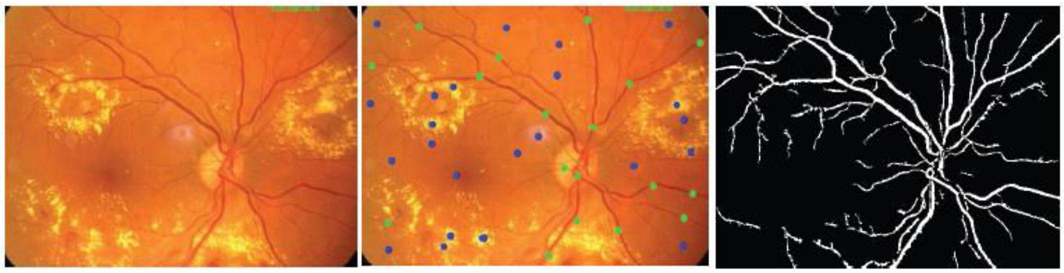


Figure. (a) Original image (b) sampling points on the original image (c) segmentation results

6. Selective sampling

In the training of the naive Bayes classifier, choosing correct training samples is important to perform an efficient segmentation process. In most of the applications, manual segmentation results are used to select training samples. Here, manual over- and under segmentation, especially in the case of narrow and small vessels, causes wrong training samples to be chosen. In this application, training samples are selected by just clicking on the image. In addition to this, a selective sampling technique is employed to choose correct training samples. Thus, the selective sampling technique eliminates the false samples that are not representing its class based on the intensity and color values of the sample that should be in an expected interval. For example, the value of feature *Rt* should be in between 0.025 and 0.55. Hence, false samples are eliminated from the training samples by using the selective sampling method. As a result, the naive Bayes classifier is trained using only correct samples to achieve a better segmentation. In addition, the training process of the naive Bayes classifier is also reduced to a few minutes by using the selective sampling technique. For further improvement, the user may also click on more (good) samples if necessary.

IMPLEMENTATION AND RESULTS

Two data sets are used for training and evaluation of the system. The TRAINING and TEST data sets that include 60 manually labeled images are used in tests. The TRAINING database consists of forty images with 768 X 584 pixels of resolution (10 for training and 10 for testing), and manually segmented forms of those images. The masks of the images were also provided for the field of view. The images were manually segmented by three ophthalmologists, two of whom segmented the test images while the other person segmented the training set. The manually segmented test set is separated into two groups, which are set A and B. Performance of the proposed system is examined on the test sets by using set A, which is employed as ground truth data.

For performance comparison, images in set B were tested against the images in set A. Apart from the TRAINING database; the TEST database includes 20 retinal images with resolution of 700 X 605 pixels. All images were manually segmented by two graders. The first grader's segmentations are chosen as ground truth data, on which the performance of the proposed system was measured.

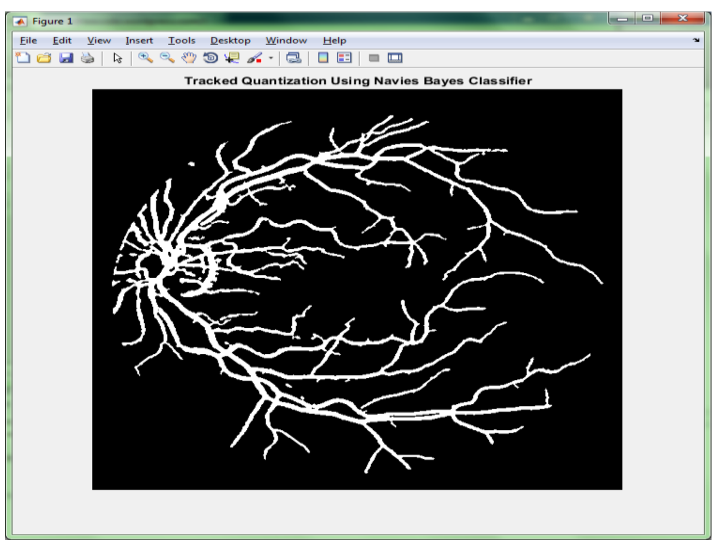
The performance of the segmentation methods are compared based on measurement tests. The methods measure overlapping and non overlapping segmentation results to determine the accuracy of segmentation results. Proposed algorithms were evaluated in terms of true positive rate, false positive rate, sensitivity, specificity, and accuracy. In most of the studies, these measurements are used to quantify segmentation results of retinal vessels. Accuracy of the segmentation result of retinal images is measured.

$$\{\mathrm{Acc}\} = (\mathrm{TS} + \mathrm{TN})/(\mathrm{TS} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})$$

Where f Acc g, TS, TN, FP, and FN represent the accuracy of segmentation results and true segmented, true negative segmented, over segmented, and under segmented pixels, respectively. Here, true segmented pixels are the overlapping pixels with the manually segmented ones and the true negative segmented pixels represent the inverse of manually segmented pixels.

A simple and fast fusion method is proposed for extracting and measuring the vessel structures in retinal fundus images. This method utilizes circular and Bayesian approaches to segment vessel structures in fundus images efficiently. Experiments and measurements were performed on a PC with Intel Core 2 Quad-2.50 GHz CPU and 4.00 GB RAM. The threshold applied in the segmentation is established based on experiments by using the training data set.

Proposed experiments prove that the proposed automatic vessel segmentation methods work tune and the system needs little adjustment to set the threshold values; it is also easily trained to achieve an efficient segmentation process. Segmentation performances of proposed methods (circular, Bayesian, hybrid-(R1) and hybrid-(R2) segmentations) are given in the first four rows of the table. These results show that the proposed method is one of most efficient methods among the unsupervised and supervised methods. The average accuracy reported for some other methods, especially for supervised methods, are relatively higher, but those methods are more complex and costly in terms of computational complexity. According to our experiments, automatic processing of an image takes less than 1 s, which takes up to 1 h in the case of manual segmentation. The proposed method shows a quite consistent and effective performance for the images with some degeneration or pathologies. The proposed methods can also easily be trained. To achieve the best performance. Sensitivity and specificity values of the hybrid method for the DRIVE and STARE data sets are 0.782 and 0.977, and 0.758 and 0.978, respectively. To present the performance of the method, sensitivity results for the DRIVE and STARE data sets for various threshold depths and various R *t* values are presented. These results show that the threshold depth and R *t* value may be chosen by the user for a better sensitivity value if necessary.



IV.CONCLUSION

The methods proposed for segmentation of retinal vessel structures in retinal images may also be used to segment other kinds of blood vessels in the detection of other diseases such as cardiovascular disease, which could be undertaken as future work. The test results also show that thin vessel structures cannot be fully detected in some cases. To improve the performance of the proposed methods, more efficient pre-processing and post processing operations may also be applied. Therefore, more efficient vessel segmentation techniques may be developed for further improvement.

FUTURE SCOPE

The methods proposed for segmentation of retinal vessel structures in retinal images may also be used to segment other kinds of blood vessels in the detection of other diseases such as cardiovascular disease, which could be undertaken as future work. The test results also show that thin vessel structures cannot be fully detected in some cases. To improve the performance of the proposed methods, more efficient preprocessing and post processing operations may also be applied. Therefore, more efficient vessel segmentation techniques may be developed for further improvement.

V. REFERRENCES

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