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Segmentation of Retinal Blood Vessels using Sub-blocking and Weighted Sum Method

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Abstract: There are various eye diseases in the patients suffering from the diabetes which includes Diabetic retinopathy, Glaucoma, Hypertension etc. These all are the most common sight threatening eye diseases due to the changes in the blood vessel structure. The proposed method using supervised methods concluded that the segmentation of the retinal blood vessels can be performed accurately using neural networks training. It uses features which includes gray level features, moment invariant based features, Gabor filtering, intensity feature, vesselness feature for feature vector computation. Then the feature vector is calculated using only the prominent features.

Keywords: Retinal blood vessel segmentation, Diabetic Retinopathy, Neural Network, Feature Vector.

I. INTRODUCTION

The retina is the only location where blood vessels can be directly visualized non-invasively in vivo. The retinal vasculature is mainly comprised of arteries and veins that are visible within the retinal image. These two spread out from the optic disc and branch successively to occupy different regions of the fundus. As they have a lower reflectance, hence they appear darker relative to the background in the color retinal image.

Fig 1.1: Original RGB Color Image

The blood vessels appear most contrasted in the green channel and it is used for automatic segmentation of vessels and the bulk of the relevant data is contained within the green channel.

Blood vessels are one of the important part of eye retina in comparison of other parts like macula, fovea, optic disc, optic cup etc. Segmentation of each part helps in the detection of any disease. Blood vessels are important as they can be viewed and analyzed directly [28].

The segmentation and analysis of retinal vasculature form an essential part of several practical applications such as detection of hypertension, diabetes, stroke and cardiovascular diseases. In case of ophthalmologic conditions, the segmentation and measurement of the retinal vessels is of primary interest in the diagnosis and treatment of a diabetic retinopathy that directly affect the morphology of the retinal vessel tree. Also the accurate segmentation of the retinal blood vessels is often an essential prerequisite step in the automated analysis of retina for characterizing the detected lesions and in identifying false positives.

Retinal blood vessels have many features such as length, tortuosity, diameter, color, width, branching pattern etc. Different eye diseases have different symptoms that aids in their detection [30]. Glaucoma can be detected by the segmentation of optic cup, DR can be detected by the segmentation of blood vessels in the fundus images, Retinal Vein occlusion shows the symptom of dilated tortuous veins, Retinal Artery Occlusion have changed colors of arteries that is copper or silver color[17].

Image segmentation has been approached from a wide variety of perspectives like - histogram thresholding, edge based segmentation, tree/graph based approaches, region growing, clustering, and probabilistic or Bayesian approaches, neural networks for segmentation, and other approaches.

DR that is caused by the untreated diabetes have the symptoms which starts from micro aneurysms which exists due to weakened capillary walls and viewed as red color small dots. Once these walls ruptured, hemorrhages appeared which are flame shaped and are of red color. When the severity of the DR increases, hard exudates appear in the retina which exists due to leakage of proteins and lipids from the blood [16]. They are yellow in color. After more advancement in severity of DR, there is obstruction in blood vessels that leads to formation of soft exudates in the form of cotton wool spots of white color. Figure 1.1 shows both healthy and pathological retina. After this neovascularization starts, in which there is abnormal growth of blood vessels at a very high speed.

There are various stages of DR which includes Non-Proliferative DR (NPDR) and Proliferative DR (PDR). NPDR is further divided into Mild, Moderate and Severe. If the disease is detected at the stage of NPDR by the accurate segmentation process, then it can be cured. Early diagnosis of DR can be done if the screening programs for segmentation are performed very effectively. But there is number of difficulties in the early diagnosis as the patients have progressive DR without symptoms of reduced vision. The severity of DR increases as there is decrease in the distance of abnormalities from the macula decreases [2].

The manual segmentation of blood vessels is very difficult and tedious task as it requires expertise since the images are very complex. Also it is very time consuming when the database is very large. There is great difficulty in measurement of various features of blood vessels which includes length, width manually. So there is a need of computer aided automatic segmentation of blood vessels with higher accuracies so that the early diagnosis of DR as well as various diseases can be performed.

II. RELATED WORK

The segmentation of blood vessels can be done through various techniques that can be broadly classified into Supervised and Unsupervised approaches. The other techniques are pattern recognition, matched filtering, vessel tracking, mathematical morphology, parallel or hardware based techniques. Supervised techniques need the images which are manually segmented for the purpose of training the system and afterwards the system is tested. Unsupervised approaches use inherent patterns to perform segmentation. All the techniques results in the classification of each pixel into either a vessel or non-vessel. All the classified vessels results in the formation of blood vessel pattern. The abnormal blood vessel pattern can help in the detection of various diseases.

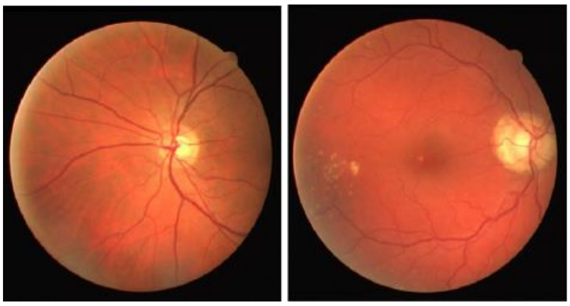

Figure 1.2 a) Healthy Retina b) Pathological Retina

GeethaRamani et al. [1] proposed a method for retinal image analysis which used both image processing and data mining techniques. Both the supervised and unsupervised learning is used to segment the retinal images for pathologies. Supervised learning is performed using Principal Component Analysis (PCA) and K-means clustering. Unsupervised learning is performed on the non-vessels from the previous steps using ensemble classification process. This method achieves higher accuracy than the previous existing methods as the classified non-vessels are processed again.

Tang et al.[2] presented a supervised classification method that is based on vessel filtering and Gabor wavelet. In this vessels are classified using the feature vectors that are formed by the vessel enhancement filtering and Gabor wavelet filtering. This filtering is unique as it is multi-scales and is performed on multiple orientations. The performance parameters clearly describe the effectiveness of the method.

Abdallah et al.[3] gave a method of segmentation of blood vessels based on multi-scale medialness which detect the vessels of similar dimensions. Hessian matrix is used to preselect the number of pixels based on their Eigen values. The gradient information of the image at any scale is computed using the response map. This method is tested on the publicly available databases for the effectiveness. Gang et al.[4] proved that the Gaussian curve is similar to the profile of blood vessels so Gaussian filtering is used for retinal vessel detection and proposed an amplitude based modified second order Gaussian filter. Aslani et al.[5] used an hybrid approach based on feature extraction for the detection of blood vessels. A 17-d feature vector was prepared consisting of responses of Gabor filter, intensity, vesselness measure. The pixels were classified using the Random Forest Classifier which has the unique features of speed, simplicity, information fusion capability etc. this method was proved superior to all state-of-the-art techniques.

Zhang et al.[6] prepared a texton dictionary for blood vessels classification. In this process, instead of manually segmented images for training, keypoints are used for training. Keypoints act as seed points for initializing the process of clustering and classification. It was proved that through this method that the keypoints based classification gives robust results as compared to hand labeled pixels.

Hassana et al.[7] uses both mathematical morphology and k-means clustering for the segmentation of blood vessels. Number of preprocessing techniques is used for enhancement of retinal blood vessels. Sinthanayothin et al. [8] proposed an identification technique based on characteristics of blood vessels which include area, shapes, and abnormal regions volumes. Vermeer et al. [9] used bee colony optimization and fuzzy c-means clustering for detection of fine and coarse vessels. Chaudhuri et al. [10] gave fastest method for detection which includes quad tree decomposition for detecting blood vessels. Chanwimaluang et al.[11] proposed a technique based on Gray Level Spatial Correlation (GLSC) method for building histograms based on image local property. Hoover et al. [12] proposed a method that helps in finding aging impact on the blood vessel segmentation. Quality of retina is affected by opacity, aging, refraction capacity etc. And also the vessel branching pattern is more visible in younger age group than in other age groups. So, this method helps in accurate segmentation in the blood vessels images of older age groups. Hughes et al.[13] proposed a filter based on key point detection and pattern recognition named as Combination of Shifted Filter Responses (COSFIRE). This method is effective in segmented the images of varying widths and having varying crossing patterns.

III. PROPOSED METHOD

The detection of retinal vessels can contribute to the mass screening of the diabetic retinopathy. First image will be normalized and green part will be extracted. The Gabor filter (serve as excellent band-pass filters for uni-dimensional signals, Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination.) will be then used to enhance the blood vessels at different orientations. All the orientation's result will be combined to get the final output. This output will be segmented based on a threshold value (need to choose a threshold value that properly separates light objects from the dark background. Image histograms provide a means to visualize the distribution of grayscale intensity values in the entire image. They are useful for estimating background values, determining thresholds, and for visualizing the effect of contrast adjustments on the image). To get the true positives, output will be masked with the mask of the image. Quantitative evaluation of this algorithm will be done by comparing the output image with the corresponding manually segmented image by human observer.

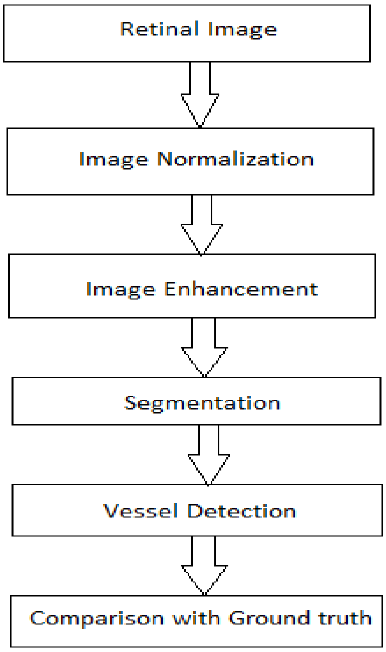

Fig: Proposed Method

IV. Proposed Algorithm

Step I: Consider the input image i.e. '.png' or '.jpg' or '.tiff'.

Step II: Read/ Load image.

Step III: Making G & B components zero to extract R component, showing R component.

Step IV: Making R & B components zero to extract G component, showing G component.

Step V: Making R & G components zero to extract B component, showing B component.

Step VI: Proceeding with G component as G has visible vessels more clear than R and B

Step VII: Applying sub blocking to extract vessels.

Step VIII: Applying weighted sum for separating background and fore ground.

Step IX*:* Applying erosion and dilation operation to smoothing.

Step X: Parameters evaluation.

As digital images are available in DRIVE, STARE ,CHASE. (publicly available databases), so available images are loaded for segmentation by applying the proposed algorithm.

DRIVE database contains the set of 40 images has been divided into a training and a test set, both containing 20 images. For the training images, a single manual segmentation of the vasculature is available. For the test cases, two manual segmentations are available; one is used as gold standard, the other one can be used to compare computer generated segmentations with those of an independent human observer. All human observers that manually segmented the vasculature were instructed and trained by an experienced ophthalmologist. They were asked to mark all pixels for which they were for at least 70% certain that they were vessel.

STARE database contains the set of 20 images for blood vessel segmentation; ten of these contain pathology. Two observers manually segmented all the images. The first observer segmented 10.4% pixels as vessels, against 14.9% vessels for the second observer.

CHASE (Child Heart an Health Study in England) contains the retinal images of both eyes of a child. This dataset includes retinal images of 9- and 10-year-old children of different ethnic origin, along with the ground truths of blood vessel segmentation as well as for vessel width measurement. The database includes images with stark differences in background levels of retinal pigmentation (being more pigmented in South Asians compared to white Europeans).

V. RESULT ANALYSIS

As the proposed technique is developed using MATLAB, its results features are explained below.

A. Load the Image

The first step in the processing phase is to load the image. The images are selected from the database. The loading of image is shown in figure 1.3.

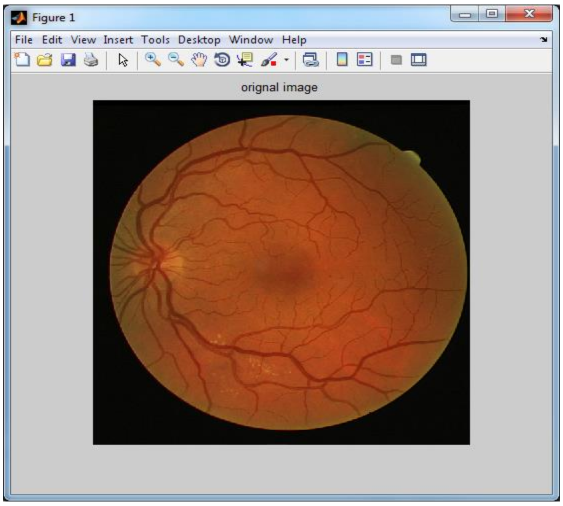

Figure 1.3: Loading of an Image

The Image is selected from the database and is being loaded for the consequent steps.

B. Extracting R G B component

Making G & B components zero to extract R component, showing R component. For showing G component, making R & B components zero to extract G component. Making R & G components zero to extract B component, showing B component. Proceeding with G component as G has visible vessels more clear than R and B. The R, G and B components are shown in Figure 1.4.

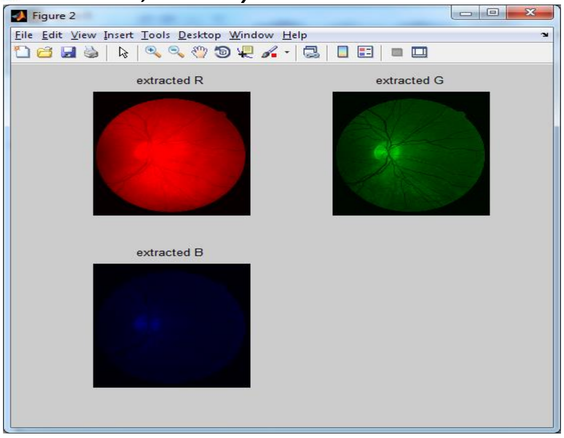

Figure 1.4: Extraction of R G B component

iii) Working with Green (G) Component:- As the G component have higher contrast than R and B and also have more visibility for blood vessels, so the further work will be done with G component.

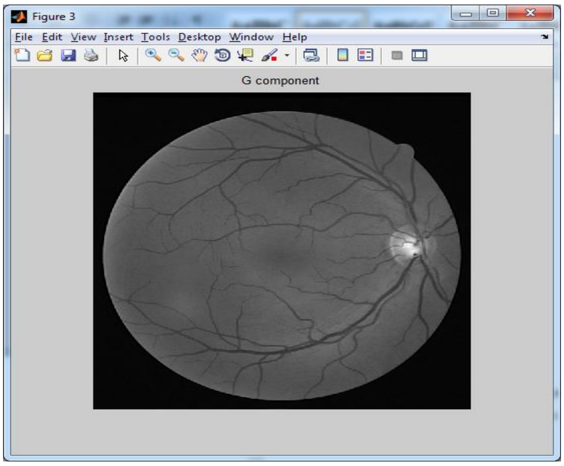

Figure 1.5: G component of retinal image

(iv) Applying sub blocking to extract vessels: An image is divided into sub-blocks and the histogram equalization is done separately for each of the blocks. After the histogram equalization the whole image is reproduced by combining the results of the sub-blocks with interpolation. The interpolation smoothly combines the sub-blocks into a whole image so that the junctions of the sub-blocks are not visible.

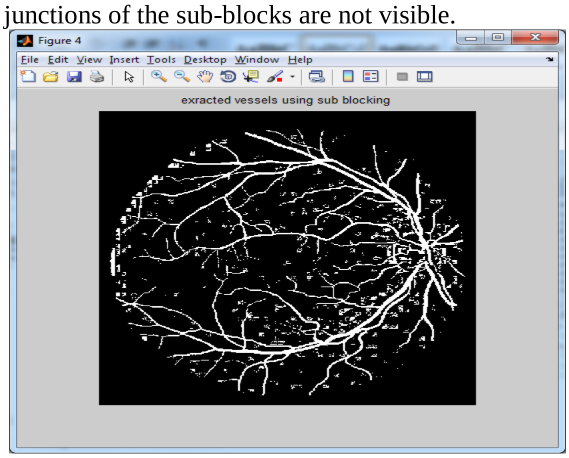

Figure 1.5: Image showing Retinal Vessels after sub-blocking

(v) Applying weighted sum method: The Weighted Sum Method is the simplest approach and probably the most widely used classical method. This method scalarizes the set of objectives into a single objective by multiplying each objective with a user supplied weight. It introduces a non-simple question: What value of the weights must be used? The answer depends on the relative importance of each objective.

Formulation:

$$F(\mathbf{x}) = \sum_{m=1}^{M} wmfm(\mathbf{x})$$
$$G(\mathbf{x}) = [g1(\mathbf{x}), g2(\mathbf{x}), \ldots, gJ(\mathbf{x})] \geq 0$$
$$H(\mathbf{x}) = [h1(\mathbf{x}), h2(\mathbf{x}), hK(\mathbf{x})] = 0$$
$$xi^{(L)} \leq xi \leq xi^{(U)}, \ i=1, N$$

- where the objectives are normalized.
- wm [0, 1] is the weight of the mth objective function.

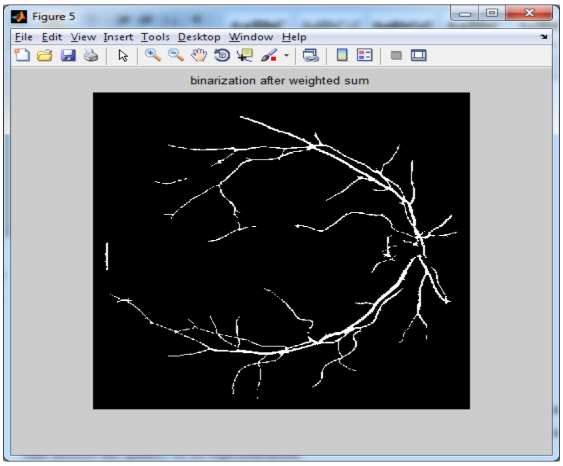

Figure 1.6:Blood vessels after Weighted Sum Metho and Binarization

(vi) Parameters Evaluation: The various publicly available databases used in this work are DRIVE (Digital Retinal Images for Vessel Extraction), STARE (Structured Analysis of the Retina) and CHASE database. The images of ground truth as well as after smoothing are shown in figure 1.7.

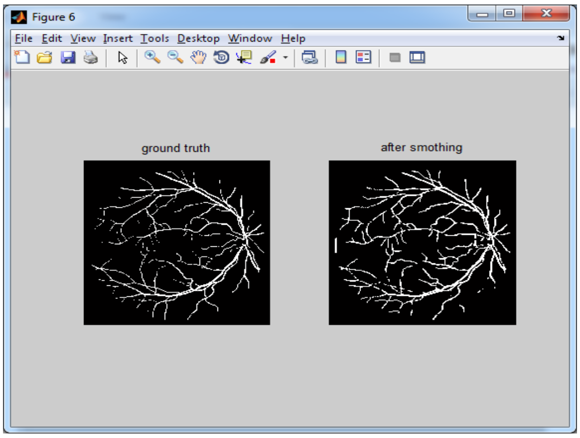

Figure 1.7: Output of Proposed Algorithm

The values of various parameters are calculated with the comparison with the values of ground truth values of DRIVE, STARE as well as CHASE database. All the three databases contain the results of manually segmented images in which the experts have segmented the pixels as vessels and non-vessels. The images in the testing database are segmented using the proposed algorithm and then the results are compared with the ground truth images given by experts. These images are compared pixel by pixel to calculate the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) which in turn will calculate the values of other parameters used for comparison which are Accuracy, Sensitivity, Specificity, Positive Predictive Value and False Predictive Value.

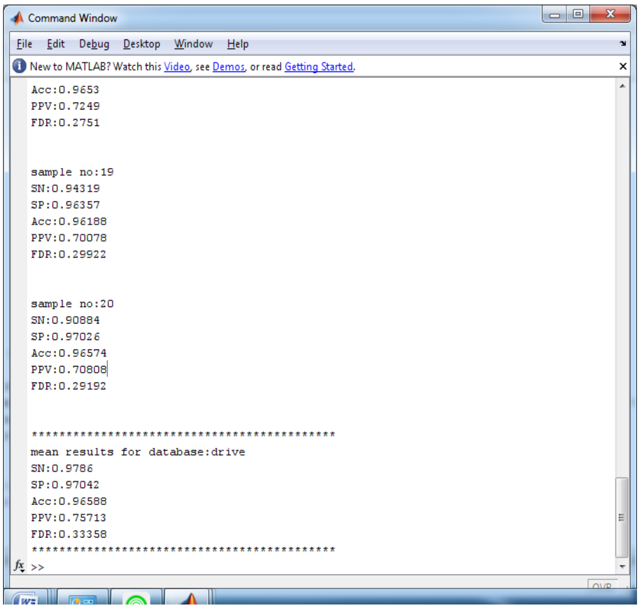

Figure 1.8:- Computation of Performance Metrics

The proposed algorithm is tested for various images in DRIVE, STARE as well as CHASE database. The results of different metrics of performance that is Accuracy, Sensitivity, Specificity, Positive Predictive Value, False Detection Rate are shown in Table 1.1

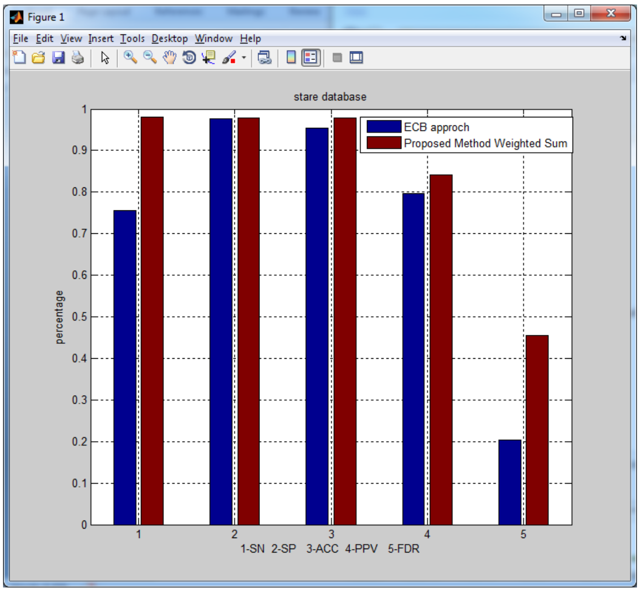

Figure 1.9: Comparison of STARE Database

Table 1.1: Comparison of results

Database	Segmentation	SN	SP	Acc	PPV	FDR
STARE	ECB Approach	0.7548	0.9763	0.9534	0.7956	43
	Proposed Method (Weighted Sum)	**0.9796**	**0.9781**	**0.9778**	**0.8412**	**0.4560**
DRIVE	ECB Approach	0.7406	**0.9807**	0.9480	**0.8532**	0.1467
	Proposed Method (Weighted Sum)	**0.9786**	0.9704	**0.9658**	0.7571	**0.3335**
CHASE	ECB Approach	0.7224	0.9711	0.9469	0.7415	0.2585
	Proposed Method (Weighted Sum)	**0.9804**	**0.9824**	**0.9803**	**0.7990**	**0.3569**

Original Image	Segmented Image
	
1.jpg	
	

2.jpg	
	
3.jpg	

VI. CONCLUSION

This research work has briefly overviewed the method for blood vessels segmentation using weighted sum method. In this, an algorithm was developed that detects blood vessels; the algorithm is proposed to detect and compare using fundus images. The proposed blood vessels detection algorithm can be used for the retinal image analysis system for clinical purposes. Firstly, the blood vessel detection process will be carried out by applying sub blocking to extract vessels. Secondly, the vessel detection process used to retrieve all vessels found it in the retina. Then the weighted sum method is used for separating background and fore ground. The obtained results are better and satisfactory.

The experimental result shows that proposed method improves the values of various parameters. The proposed method outperforms for many test images.

This thesis work had concluded that:

a) A weighted sum method technique is the efficient and fast method for vessel detection of fundus images.
b) The proposed algorithm gives better results of images and their parameters.

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