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A Review of Retinal Vessel Segmentation Techniques

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***Abstract*: Retinal vessels plays a very important role in many applications such as detecting various diseases such as diabetic retinopathy, hypertension etc apart from being used in biometrics. Efficient extraction of retinal blood vessels is very important as more accurate the extraction is, the better the decisions can be made. This paper discusses various retinal vessel segmentation techniques developed so far.**
***Keywords*: Retina, Blood Vessels, Segmentation, Extraction, Diabetic Retinopathy.**

I. INTRODUCTION

Blood vessel segmentation is a sequential process in which first of all the retinal image is converted into a grayscale image. This gray-scale image is then enhanced to improve its visual quality because an enhanced image can be better segmented to extract blood vessels. So after enhancement, image segmentation is done and a binary image is obtained through thresholding. Once vessels are extracted, they have some missing pixels, so post processing is performed to fill these missing pixels. It is shown in the following figure [1].

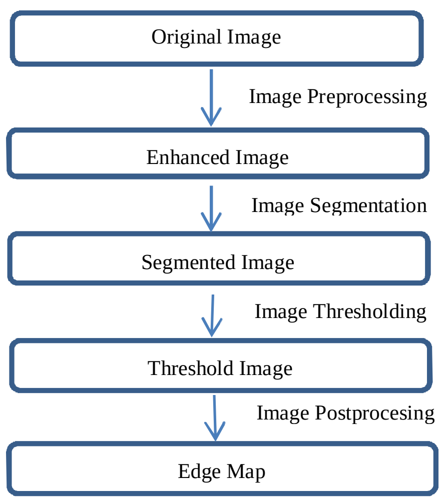

Fig.1. Stages of blood vessel extraction

II. LITERATURE REVIEW

Shahab et. al.[2] combined a set of robust features from different algorithms to form a feature vector for pixel classification. The feature vector is 17-D vector that consists of 13 Gabor features apart from intensity, vesselness measure, intensity of top hat transformed image and response of B-COSFIRE filter. Random forest classifier is used to classify the pixels that whether it is a vessel pixel or a non-vessel pixel. The databases used are STARE and DRIVE. Accuracy obtained by this method is 0.9513 and 0.9605 for DRIVE and STARE databases respectively. The most important aspect of this method is that the method is very robust and perform with very high accuracy even in case of cross training case. Another strong point of this method is that it works fairly well even for pathological images in which the other methods usually fail. This method is has a little downside also that it is bit less efficient is the sense that it computes 17 features for which it has to perform high computations thus reducing the overall accuracy in terms of speed.

Syed Ayaz et al. [3] proposed a new algorithm of blood vessel segmentation based on regional and Hessian features for image analysis in retinal abnormality diagnosis. In it a lot of emphasis is given on image enhancement. A 24-D feature vector is used to classify the pixels. LMSE (linear minimum squared error) classifier was used for the classification purposes. The algorithm was applied on the DRIVE database and an accuracy of 0.9479 and sensitivity of 0.7205 is obtained. This algorithm is particularly good at detecting blood vessels at the peripapillary region with a limitation that such a huge feature vector needs lots of computational time.

Roberto et al [4] devised an unsupervised technique for retinal vessel segmentation especially in pathological images. A Neighbourhood Estimator Before Filling (NEBF) filter is used to inpaint the missing pixels. All the exudates are removed before enhancing the vessels using the multiple-scale Hessian approach. The databases used in the work are STARE and HRF. An accuracy of 0.9562 and 0.9581 is achieved in STARE and HRF respectively. The technique provides really good results both quantitatively and qualitatively but it has a drawback that short vessels may be lost by the application of the NEBF filter. This model is not suitable for the retinal adversaries including the drusen or haemorrhages, where it carries the possibility of producing the higher number of false positive cases, which eventually degrades the overall performance of the proposed model. The smart inpainting models can be used for the elimination of the damaged retinal parts due to the drusen or haemorrhages based adversaries.

L Zhang et al [5] proposed a technique that used texton dictionary for pixel classification. In it key points are determined using gabor filter bank and SIFT algorithm. Seed point is used to begin the algorithm using k-means clustering algorithm. Neural Network classifier is used to classify pixels as either vessel pixels or non-vessel pixels. DRIVE database is used in this work. Sensitivity, Specificity and Accuracy of 0.7812, 0.9668 and 0.9505 respectively is obtained using this technique. The advantage of this technique is that it mitigates the problems arising due to observer variability.

Wang et al [6] incorporates the ensemble feature based blood vessel pattern extraction in the hierarchical fashion. The segmentation method for the retinal vessel pattern utilizes the classical combination of the classification models of convolution neural network (CNN) and random forest (RF) models. The feature learning is performed using the convolution neural network method, which is followed by the training and testing model based upon the random forest classification model. The proposed model is known to offer higher than 97% accuracy over the STARE and DRIVE databases. The training time for one ephoc is very high, which has been recorded at 2 hours, whereas the convolution neural network is trained with only 100 ephocs (rotations) accounting for nearly 8 days, which makes it massive system and adaptable to the cloud hosting models. In order to realize the quick response feature extraction model, the feature extraction can be processed using Genetic programming or other optimization (Swarm intelligence) algorithms. The advantage that this method offers is that it gives the multi scale information about the retina as it not only uses the output of the last layer but also of the intermediate layers.

Chakraborti et al [7] has developed the vessel pattern extraction filter with the self-adaption capability to the variations in the retinal samples. The pertaining combination of the highly sensitive vessel extraction filter along with histogram orientation method has been realized for the purpose of vessel structure extraction. The Hessian matrix has been applied over the Eigen-analysis programmed in the different intensity based scales, which further undergoes the variable intensity ranges. The scalable Gaussian filtering has been arranged in the linear fashion over the pre-processed samples with Eigen-analysis using Hessian Matrix for the precision based pattern outlining. The lower value of the Sensitivity parameter (72% for DRIVE database, 67% for STARE database & 53% for CHASE database) indicates the presence of false negative cases in the higher density, which is the possible area of improvement in order to create the robust blood vessel extraction method.

Imani et al [8] has worked towards the improvement in the morphological models for the extraction of retinal blood vessels. The morphological model offers the morphological component analysis (MCA), which improvises the blood vessel pattern in the retinal imagery. The use of Morlet wavelet transform (MWT) for the feature enhancement purposes, which finalizes the features over the output obtained from the MCA based component analysis & vessel structure extraction. The retinal extraction ensemble model combining the morphological component analysis & Morlet wavelet transform has been designed to lower the false positive cases to achieve the higher accuracy, which has been recorded slightly higher than 95% over the DRIVE & STARE databases. The MCA algorithm has spotting returning lower accuracy over the diabetic (high severity level) samples, which contains the damaged visible features or the lesions. Afterwards, the proposed model has achieved the higher accuracy at 95% level. The hand-drawn sample pattern based dictionary set can be utilized for further improvement rather than the transformation determination for extraction of the blood vessels. The advantage of this algorithm is that it can easily separate blood vessels from lesions which improves overall accuracy of the algorithm.

C Zhu et al [9] proposed a supervised method for retinal vessel segmentation using Extreme Learning Machine (ELM). In it a 39-D feature vector is used consisting of local features, morphological features, phase congruency. Feature vectors and manual labels act as an input to the classifier. ELM gives a binary image as an output. The algorithm gives an average accuracy, sensitivity, and specificity are 0.9607, 0.7140 and 0.9868 respectively on DRIVE database. Phase concurrency is used in this method to increase robustness of the algorithm. The advantage of this technique is that although it is a supervised method, it takes less training and testing time using ELM classifier than other supervised methods.

M Javidi et al [10] proposed a vessel segmentation and microaneurysm technique using dictionary learning. The biggest benefit of this technique is that it creates dictionary using learning rather than fixed dictionary which was commonly used to extract vessels. This technique works well specially for abnormal images. It is a novel technique based on discriminative dictionary learning and sparse coding. Accuracy of the proposed technique on both DRIVE and STARE databases is 0.9446 and 0.9517 respectively. The advantage of this technique is that it achieves high accuracy especially in severe diabetic retinopathy images.

Fraz et al [11] used centreline detection and bit plane slicing for retinal vessel segmentation. First order Gaussian derivatives are used for centreline detection. An orientation map is obtained using top hat morphological operation. The map is then combined with the Gaussian derivatives to obtain the segmented tree. An average accuracy of 0.9430, 0.9442 and 0.9579 is obtained in DRIVE, STARE and MESSIDOR databases. This technique works well for Gaussian shaped profile of vessels. However this technique gives low accuracy if there is presence of light reflexes, especially in the images of young participants.

Wilfred et al [12] proposed a novel method to analyse vascular structure of the retina. Neural network is used to classify pixels. Gabor and moment invariant based features act as an input to the neural network which classify a pixel as either a vessel pixel or a non-vessel pixel. One of the drawback of this algorithm is that it misses the detection of thin vessels which can be compensated using an enhancement algorithm.

III. PERFORMANCE EVALUATION

The algorithms are tested most commonly on the publicly available DRIVE [13] and STARE [14] databases. DRIVE database consist of 40 images, with 20 images in test set and 20 images in training set with the resolution of 768 * 584 for each image. There are 20 images in the STARE database and each image has a resolution of 700 * 605. The metrics used for evaluation are Sensitivity, Specificity and Accuracy. Sensitivity is the ratio of pixels that have been truly classified as vessel pixels.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

Where TP is the no. of pixels classified as vessel pixels and FN are the no. of pixels that have falsely classified as non-vessel pixels. Specificity is the ratio of pixels that have been truly classified as non-vessel pixels.

$$\text{Specificity} = \frac{TN}{FP + TN}$$

Where TN is truly classified pixels that are non-vessel pixels. Accuracy is the ratio of pixels that correctly classified as either vessel or non-vessel pixels.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

IV. COMPARATIVE ANALYSIS

TABLE I: COMPARATIVE ANALYSIS OF VARIOUS TECHNIQUES

Segmentation Technique	Accuracy	Sensitivity	Specificity	Remark
Shahab et. al.[2]	0.9513(DRIVE), 0.9605 (STARE)	--	--	1. Very Robust 2. Works well for pathological images 3. Efficiency is a concern
Syed Ayaz et al. [3]	0.9479 (DRIVE)	0.7205	--	1. Good at detecting vessels at peripepillary regions 2. High computational time
Roberto et al [4]	0.9562(STARE), 0.9581(HRF)	--	--	1. The technique is not good for pathological images.
L Zhang et al [5]	0.9505	0.7812	0.9668	1. Mitigates the observer invariability.
Wang et al [6]	0.97(DRIVE), 0.97(STARE)	--	--	1. Gives multiscale information about the retina
Chakraborti et al [7]	--	0.72(DRIVE), 0.67(STARE),	--	--

		0.53(CHASE)		
Imani et al [8]	0.9523(DRIVE), 0.9590(STARE)	0.7524(DRIVE), 0.7502(STARE)	0.9753(DRIVE), 0.9745(STARE)	1.The algorithm can easily differentiate between vessels and other regions and improve accuracy.
C Zhu et al [9]	0.9607(DRIVE)	0.7140(DRIVE)	0.9868(DRIVE)	1. Robust 2. Less Computation time
M Javidi et al [10]	0.9446(DRIVE), 0.9517(STARE)	--	--	1. Works well for pathological images.
Fraz et al [11]	0.9430(DRIVE), 0.9442(STARE), 0.9579(MESIDOR)	--	--	1. Struggle in the presence of light reflexes.

V. CONCLUSION

In this paper various retinal vessel segmentation techniques have been discussed along with their strong and weak points. It has been observed that the presence of various factors such as light reflexes or other pathological disorders can severely hamper the accurate extraction of blood vessels. It has also been observed that high accuracy can be achieved using large feature vectors with a downside that as the size of the feature vector increases the algorithm becomes slow. There is a need to identify the important and necessary set of features to create the feature vector so that high extraction accuracy can be achieved in a very short span of time.

REFERENCES

[1] Singh et al, "A Survey on Blood Vessel Segmentation Methods in Retinal Images", EDCAV, 2015.
[2] Shahab Aslani et al., "A new supervised retinal vessel segmentation method based on robust hybrid features", Biomedical Signal Processing and Control 30 (2016) 1–12.
[3] Syed Ayaz et al., "Blood vessel segmentation in color fundus images based on regional and Hessian features", Graefes Arch Clin Exp Ophthalmol, 2017.
[4] Roberto et al, "Leveraging Multiscale Hessian-based Enhancement with a Novel Exudate Inpainting Technique for Retinal Vessel Segmentation", IEEE Journal of Biomedical and Health Informatics, 2015.
[5] Lei Zhang et al, "Retinal vessel segmentation using multi-scale textons derived from keypoint", Computerized Medical Imaging and Graphics, 2015.
[6] Shuangling Wang et al, "Hierarchical retinal blood vessel segmentation based on feature and ensemble learning", Neurocomputing, 2014.
[7] Tapabrata Chakraborti et a;, "A self-adaptive matched filter for retinal blood vessel detection", Machine Vision and Applications, 2014.
[8] Elaheh Imani," Improvement of Retinal Blood Vessel Detection Using Morphological Component Analysis", Computer Methods and Programs in Biomedicine, 2015.
[9] C Zhu et. al., "Retinal vessel segmentation in colour fundus images using Extreme Learning Machine", Computerized Medical Imaging and Graphics, 2016.
[10] M Javidi, "Vessel segmentation and microaneurysm detection using discriminative dictionary learning and sparse representation", Computer Methods and Programs in Biomedicine, 2016.
[11] Fraz et al, "An approach to localize the retinal blood vessels using bit planes and centerline detection", computer methods and programs in biomedicine 108 (2012) 600–616.
[12] Wilfred et al, "Retinal vessel segmentation employing ANN technique by Gabor and moment invariants-based features", Applied Soft Computing 22 (2014) 94–100.
[13] Research Section, Digital Retinal Image for Vessel Extraction (DRIVE) Database. Utrecht, The Netherlands, Univ. Med. Center Utrecht, Image Sci.Inst.[Online].Available:http://www.isi.uu.nl/Research/Databases/DR IVE.
[14] STARE Project Website. Clemson, SC, Clemson