Retinal Vasculature Segmentation in Smartphone Ophthalmoscope Images

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Abstract— **Retinal imaging system assists ophthalmologists to diagnose the diseases and to monitor the treatment processes. Conventionally, fundus retinal images are obtained from expensive systems like fluorescein angiography and fundus photography but these systems are large tabletop units and can only be handled by trained technicians. Hence, this study reports a low cost, compact and user friendly smartphone ophthalmoscope to perform indirect ophthalmoscopy. By using this system, initial and periodic screening of retina (both center and periphery regions) becomes easier. Traditionally, retinal diseases are diagnosed by manual observations of fundus images and it is a time consuming process. So, automatic retinal disease diagnosing systems are introduced by extracting the essential features of the fundus retinal images. One of the most essential features of the retina is the blood vessels as its morphological changes helps in diagnosing the retinal diseases. Hence, in this study blood vessels are extracted from smartphone ophthalmoscope (SO) images using level set method to develop an automatic retinal disease diagnosing systems for ophthalmologists. The performance of the retinal vasculature segmentation algorithm is compared and analyzed on DRIVE database of retinal images and on smartphone ophthalmoscope images using the measures like sensitivity, specificity and accuracy level.**

Keywords— **Smartphone ophthalmoscope, K-means, Total variation filtering, Bottom-hat transformation, Level set technique**

I. Introduction

Retina is the light sensitive layer of an eye which helps in vision. Retina can be imaged using fundus photography and the images from this system provides complete information about the features like optic disk, macula, fovea and blood vessels and thus it helps in identifying the retinal diseases. By extracting these features early stages of the retinal diseases can be identified. To diagnose the early stages of the disease, periodic screening of the retina is required. As the cost of imaging the retina becomes costlier using the available retinal imaging systems, periodic screening of the retina becomes difficult by common people. Hence, in this study to reduce the cost of imaging the retina a low cost smartphone ophthalmoscope is introduced after referring to the research conducted by Haddock et al. [1] and Myung et al. [2]. The traditional way of diagnosing the diseases by physician using the fundus images consumes time and involves human errors. This ended up in developing an automatic disease diagnosing system. This system extracts the essential features of the retina and helps in identifying the morphological changes developed in them. Hence, this study reports that the blood vessels are extracted to diagnose the severity of the retinal diseases. This can be done by identifying the morphological changes of blood vessels like vessel shape and length. The retinal image acquired from the SO is affected by noises and hence requires noise filters to remove them. In literature, it is reported that the non-linear filters are better denoising techniques than linear filters as they preserves edge details. Hence, a popular non-linear total variation denoising technique is selected for this study and observed that the noises are smoothened out in the flat regions and preserves fine edges even under low signal to noise ratio [4]. Recently, to segment the blood vessels level set methods are used. In this study, a level set method [7] which considers the objects region information to extract the blood vessels is selected and tested for its performance.

II. Materials and methods

In this section, we present the smartphone ophthalmoscope system setup and elaborate on the retinal vasculature segmentation algorithm.

A. System Design

In this study, smartphone ophthalmoscope is developed using a smartphone in conjunction with a 20D condensing lens. Here, smartphone iPhone 4s is used to capture and store the retinal images. And the 20D condenser lens is used for obtaining 20° field of view to image the retina. It is being proved that the smartphone ophthalmoscope can be used as an initial screening tool for diagnosing the retinal diseases [3]. This system uses the coaxial light source of the iPhone and captures the digital image of the retina. This system basically works like an indirect ophthalmoscope. Fig. 2 (a) represents the setup developed to image the retina.

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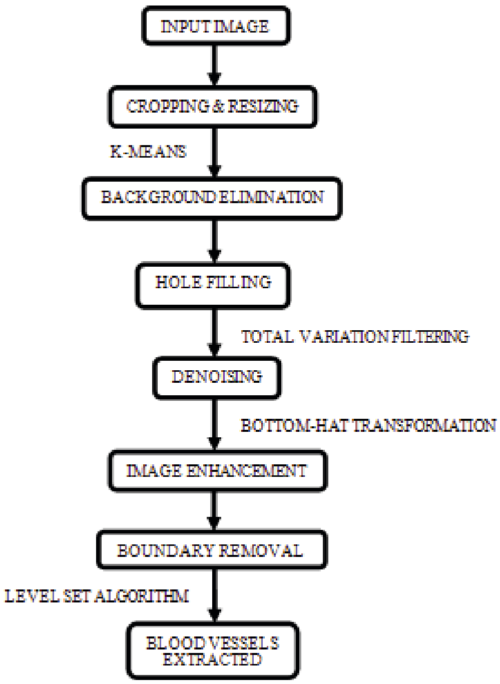


Fig. 1 Process flow to segment blood vessels

Here, approximately the distance between the lens and the smartphone is fixed to 11.5 cm and it can be varied if necessary. Always, the distance between the object and the lens is kept greater than 5 cm to obtain magnified fundus images. Imaging the retina using this setup is possible only by dilating the pupil of the subjects.

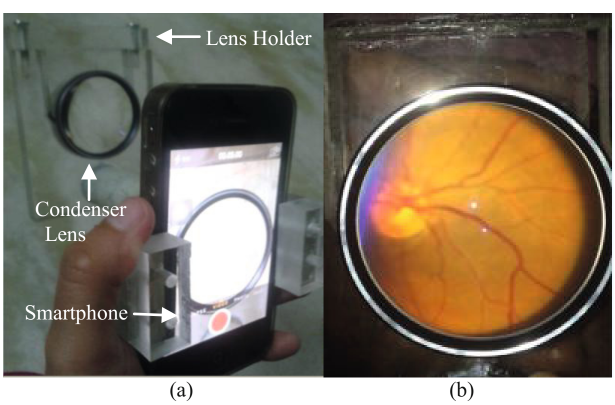


Fig. 2 (a) Smartphone ophthalmoscope setup (b) A smartphone ophthalmoscope retinal image

B. Retinal Vasculature Segmentation Algorithm

The images acquired from this system are processed in MATLAB R2013a software to segment the blood vessels. Fig. 1 gives the process flow to segment the blood vessels from the database and from the smartphone ophthalmoscope images (SO).

Preprocessing Stage: Preprocessing steps are performed to improve the quality of the fundus retinal images. Thus, in this study the images acquired are cropped and resized to half the size of the original image to reduce the computation. Then, the unwanted background details were removed using k-means algorithm [5]. Here, Fig. 3 shows the background eliminated images. After performing this technique holes are being introduced in the images. Therefore, these holes are filled by using hole filling operation. The resulting image after this process might be affected with noises and hence the total variation filtering technique is used to remove these noises. The denoised image is then enhanced by applying the bottom-hat morphological transformation to enhance the blood vessels alone.

Background Elimination: K-means algorithm is used for background elimination. It is one of the unsupervised clustering techniques used to group the given random data's into different clusters.

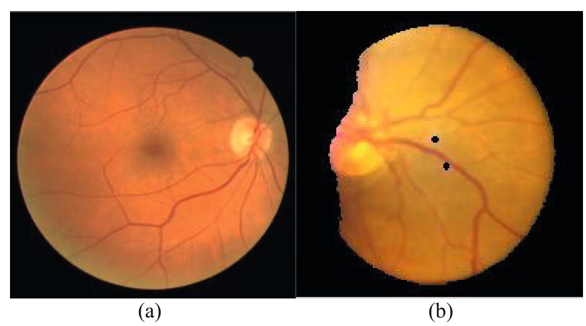


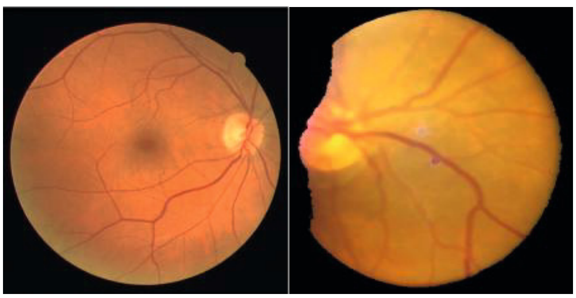
Fig. 3 Background eliminated images (a) Database image & (b) Smartphone ophthalmoscope image (holes might be generated in this step)

This algorithm extracts only the colour information (RGB). Before performing k-means clustering technique, given RGB image is transformed into L*a*b* color space such that only the colour information are grouped together and helps in the clustering process. After this process, clusters are randomly initialized. Then the data sets are labeled to the closer cluster. Finally, index is calculated for each cluster. Every data set is labeled with its cluster index. And the last two steps are repeated until there is no more move of the data points to different clusters.

Total Variation Minimization: One of the most popular non-linear denoising techniques is the total variation (TV) denoising filter. TV is based on the principle that images with high energy details have high total variation and this variation of the image can be reduced by finding the closeness to the original image [4].

$$J(u) = R(u) + \frac{\lambda}{2} ||Tu_{ij} - y||_2^2 \quad (1)$$
$$R(u) = \sum_{1 \le i,j \le N} |\nabla u_{i,j}| \quad (2)$$

Here, y is the given noisy image; T is the linear operator and u_{ij} is the unknown image. So, to get denoised image u_{ij} both the TV-norm i.e. R (u) and the fidelity term have to be minimized. But, when both the terms are minimized simultaneously, proper denoising cannot be achieved. Hence, by adjusting the regularization parameter, λ both the TV-norm and fidelity term can be minimized such that the resulting denoised image is as close as that of the original image.



(a) (b)

Fig. 4 Denoised images (a) Database image & (b) Smartphone ophthalmoscope image

In order to verify the efficiency of the TV algorithm quantitatively, PSNR values are computed for 12 smartphone ophthalmoscope images and it is observed that the average PSNR value as 39.83 dB. Fig. 4 shows the denoised images after TV filtering.

Image Enhancement: To extract the blood vessels effectively, bottom-hat transformation is performed. This helps in enhancing the blood vessels from the other details in an image as they are the darkest region in an image. After performing bottom-hat transformation [6], only the green channel is extracted as it contains almost all the blood vessel details in an image. Fig. 5 shows the enhanced database and smartphone ophthalmoscope images after performing bottom-hat transformation and green plane extraction.

Retinal Vasculature Segmentation Algorithm: In recent years, segmentation is performed using level set methods. This technique was first introduced by Sethian et.al and then improvised by Chan et al. [7]. This method segments (Fig. 6 segmented images) an object by finding minimization of energy. The energy equation is defined by this algorithm is,

$$E(C, c_1, c_2) = \mu\, Length(C) + \nu\, Area\big(inside(C)\big) + \lambda_1 \int_{inside\ (C)} |u_0(x,y) - c_1|^2\, dxdy + \lambda_2 \int_{outside\ (C)} |u_0(x,y) - c|^2\, dxdy \quad (3)$$

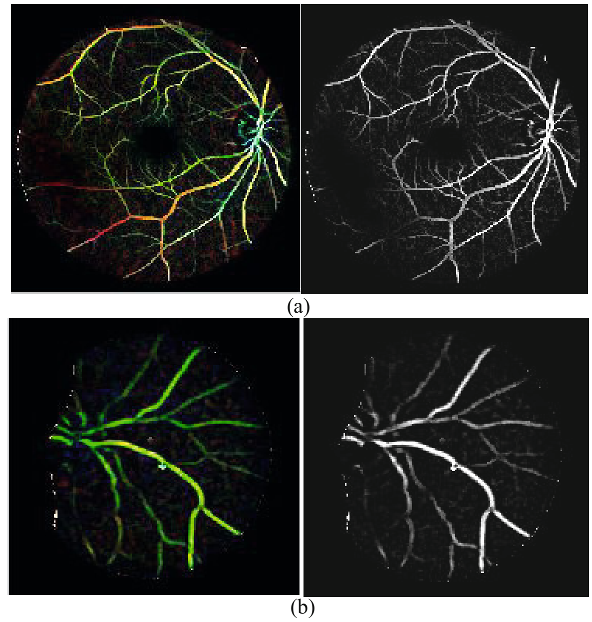
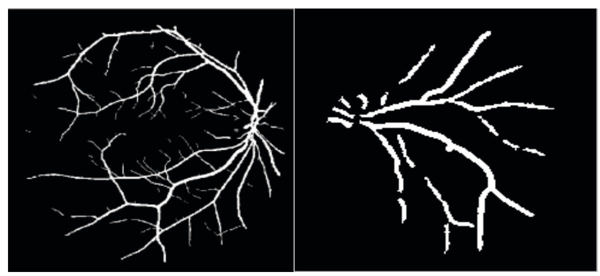


Fig. 5 Bottom-hat transformed image & green plane extracted image (a) Database & (b) Smartphone ophthalmoscope image



(a) (b)

Fig. 6 Shows, the segmented blood vessels after applying Level set method in (a) Database image & (b) SO image.

Where, $u_0(x,y)$ is the given image, C is the evolving curve and c_1, c_2 are the constants representing the average pixel values inside C and outside C. $\mu \ge 0$, $\nu \ge 0$ and $\lambda_1, \lambda_2 > 0$ are fixed parameters [7]. Assuming that the level set function ϕ defines the evolving curve C.

$$C = \phi\,(x,y) = 0$$
$$inside(C) = \phi\,(x,y) > 0$$
$$Outside(C) = \phi\,(x,y) < 0 \quad (4)$$

By using the known Heaviside function, H and Dirac measure, δ_0 energy equation is rewritten as [7],

$$E(\phi, c_1, c_2) = \mu \int_{\Omega} \delta_0(\phi(x,y)) |\nabla\phi(x,y)| dxdy + \nu \int_{\Omega} H(\phi(x,y)) dxdy + \lambda_1 \int_{\Omega} |u_0(x,y) - c_1|^2 \, H(\phi(x,y)) dxdy + \lambda_2 \int_{\Omega} |u_0(x,y) - c_2|^2 \, H(1-\phi(x,y)) dxdy \quad (5)$$

III. Results

The performance of the proposed algorithm is tested with DRIVE database. To obtain the statistical quality metrics such as sensitivity (Sen), specificity (Spe) and accuracy (Ac) the segmented blood vessels using the proposed algorithm are compared with the ground truth of the respective fundus images in the DRIVE database.

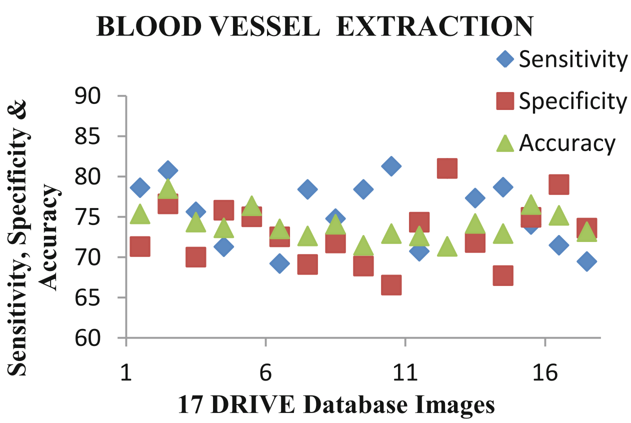


Fig. 7 Statistical quality metrics for 17 DRIVE database images

TP refers to a pixel labeled as vessel by both the proposed algorithm and the ground truth, while TN refers to a pixel that is considered to be non-vessel by both.

$$Sen = \left(\frac{TP}{TP+FN}\right) X\ 100, \qquad Spe = \left(\frac{TN}{TN+FP}\right) X\ 100,$$

$$Ac = \left(\frac{TP+TN}{TP+FP+TN+FN}\right) X\ 100 \quad (7)$$

FN refers to pixels of vessels in the ground truth and missed by the proposed algorithm, and FP refers to pixels falsely considered by the proposed algorithm as vessel. Statistical metric results for 17 DRIVE database images are reported in the Fig. 7. This figure reports that the 17 DRIVE database images has the sensitivity range from 69% to 81%, specificity range from 66% to 76% and accuracy range from 71% to 78%. The average accuracy of the algorithm is 74%.

IV. Conclusions

In this study, smartphone ophthalmoscope is developed and used to image the center and periphery region of the retina. This work also reports that the level set algorithm is used to extract the blood vessels automatically both in database and SO images. Presently, we are trying with different blood vessels enhancement techniques to improve the accuracy of the algorithm.

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Conflict of Interest

There are no conflicts of interest.

References

1. L. J. Haddock, D. Y. Kim, and S. Mukai (2013), ‘Simple, inexpensive technique for high-quality smartphone fundus photography in human and animal eyes,’ *J. Ophthalmol.*, vol. 2013, pp. 1–6.
2. D. Myung, A. Jais, L. He, M. S. Blumenkranz, and R. T. Chang (2014), ‘3D Printed Smartphone Indirect Lens Adapter for Rapid, High Quality Retinal Imaging,’ *J. Mob. Technol. Med.*, vol. 3, no. 1, pp. 9–15.
3. Andrea Russo, Francesco Morescalchi, Ciro Costagliola, Luisa Delcassi and Francesco Semeraro (2014), ‘Comparison of Smartphone Ophthalmoscopy With Slit-Lamp Biomicroscopy for Grading Diabetic Retinopathy,’ *American J. of Ophthalmol.*, vol. 159, no. 2, pp. 360-364.
4. M. J. Bioucas-dias, A. M. Figueiredo, and P. J. Oliveira (2004), ‘Total Variation-Based Image Deconvolution: A Majorization-Minimization Approach,’ *in IEEE International Conference on Acoustics, Speech and Signal Processing*, no. 2, pp. 1–5.
5. S. R. Dubey, P. Dixit, N. Singh, and J. P. Gupta (2013), ‘Infected Fruit Part Detection using K-Means Clustering Segmentation Technique,’ *Int. J. Interact. Multimed. Artif. Intell.*, vol. 2, no. 2, pp. 65-72.
6. A. F. M. Hani, L. I. Izhar, and H. a Nugroho (2009), ‘Analysis of Foveal Avascular Zone in Color Fundus Image for Grading of Diabetic Retinopathy,’ *Int. J. Recent Trends Eng.*, vol. 2, no. 6, pp. 101–104.
7. T. F. Chan and L. a. Vese (2001), ‘Active contours without edges,’ *IEEE Trans. Image Process.*, vol. 10, no. 2, pp. 266–277.

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