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Retinal Blood Vessel Segmentation for Assessment of Diabetic Retinopathy Using a Two-Dimensional Model

C. Jayakumari and T. Santhanam
D.G. Vaishnav College, Arumbakkam, Chennai, Tamil Nadu, India

Abstract: Retinal blood vessels are very imperative structures in ophthalmologic images. Automated image processing has the immense potential to assist the physicians in the early detection of diabetes, by observing the changes in blood vessel patterns in the retina. This study details a novel vessel tracking algorithm as a part of the set of tools exercised for the automated diagnosis of diabetic retinopathy. To begin with, the papilla is detected by utilizing Canny's edge detection algorithm. Then, the blood vessels are traced by using the second-order derivative Gaussian filter. The projected algorithm has achieved acceptable results to spot the small veins/thin vessels that play a mighty contribution in the clinical arena.

Key words: Vessel extraction, vessel tracing, gaussian second derivate, two-dimensional model, segmentation

INTRODUCTION

Diabetic Retinopathy (DR) is a consequence of long term diabetes mellitus, one of the foremost reasons of blindness. Kanski (1994) has detailed DR causes pathological changes of the retinal vessel tree such as microaneurysms, intraretinal microvascular abnormalities, venous beading, neovascularisations and as well as haemorrhages, exudates and retinal oedema. This abnormality detection in images is expected to play a predominant role in many real-life applications.

One of the solutions for diabetic retinopathy engrosses screening of medical images. A swift, supreme and steady method for abnormality finding in images will greatly help to enhance the health-care screening process. In order to evaluate the growth of the retina status, image processing techniques are required to extract the relevant quantitative data about changes of the retinal vessel tree.

Retinal vessel segmentation routine can be split into two major classes namely detection and tracking. Detection schemes are generally bottom-up approaches that make few initial assumptions about the global structure of the vascular tree and most of the researchers have employed edge-finding or region-growing algorithms for edge detection. These algorithms traverse the entire image to find all candidate regions. On the other hand, a vessel tracking algorithms rely heavily on several anatomic assumptions like connected vessels, vessel convergence on optic disk etc. Akita *et al*. (1982, 1981) has detailed that they are competent of extracting features regarding the vessel course and contour, which are then examined by the ophthalmologist for automatic recognition of vascular changes specifically vasoconstrictions, vasodilatations, venous beading and new vessels.

Numerous methods for segmenting blood vessels using rule based and supervised are reported in Sinthanayothin *et al*. (1999) and Staal *et al*. (2004) and has sketched a relaxation method that discriminates between artery and vein. Use of multiscale filtering has been proposed for segmentation of curvilinear structures in three-dimensional medical images by Sato *et al*. (1998). Michal *et al*. (2006) has explored the likelihood of applying Multiscale Matched Filters for blood vessel tracking. Chaudhuri *et al*. (1989) has deployed two dimensional matched filters to trace the blood vessels. The applicability of steerable filters to several applications in general and blood vessels in particular has been described in Freeman *et al*. (1991). Further they have stated that with a set of basis filters, one can adaptively steer a filter along any direction. They designed a set of such steerable filters based on directional derivatives of Gaussians and employed these filters and their Hilbert transforms to compute local direction maps. The usages of wavelet local maxima across scales which characterize the local shape of irregular structures have been presented by Stephane *et al*. (1992). Hoover *et al*. (2000) have investigated the handling of local and global vessel features to segment the vessel network. Leandro *et al*. (2003) have explored the use of two dimensional continuous wavelet transform and supervised pixel classification. Cornforth *et al*. (2001) has cited about the

Corresponding Author: T. Santhanam, D.G. Vaishnav College, Arumbakkam, Chennai, Tamil Nadu, India

usage of wavelet analysis, supervised classifier probabilities and adaptive threshold procedures, as well as morphology-based techniques.

In this research, an attempt has been made to present an algorithm that can be made part of automating the diagnostic tools needed for early diagnosis of diabetes in retinal pathology. The main aim of this study is to publicize the segmentation of optic disc and blood vessels for recognizing the veins. The algorithm has worked well to establish small thin vessels in the retina.

SEGMENTATION

Accurate and automatic segmentation of images is an important step in image processing. Segmentation of images is a subjective and context-dependent cognitive process. It implicitly contains not only the detection and localization of the object chosen (i.e. blood vessel) but also the delineation of the activated region. In the field of medical imaging, the precise and programmed delineation of anatomic structures from the image data sequences is worth an open problem to explore. Innumerable techniques have been deployed, but as a rule, user interaction cannot be negated or the process is said to be robust only for unique kinds of images.

Color component: Color images represent vital information about the perceptual content of a certain image. The color of any image can be realized in different ways and the color models are typically based on physical, physiological and technical aspects. The human eye perceives color reaction through a mix of red, green and blue signals. As a rule of thumb, each color can be mixed one and only with these 3 primary colors. When the RGB components of the non-mydriatic images are visualized discretely, the green channel represents the premium vessel/background contrast, whereas, the red and blue channels depict low quality contrast and are noisy too.

Zheng *et al*. (1997) has detailed that the green channel has been singled out to create the feature vector itself, i.e. the green channel intensity of each pixel is taken as one of its features. Figure 1 exhibit the image information in different channels and it is very obvious that the green channel out performs the other channels in terms of contrast and thus considered for segmentation of blood vessels. Even though the contribution of red channel is minimal in the case of segmentation of blood vessels, its role is very significant in localizing the optic disc because of the nonappearance of blood vessels inside the red component.

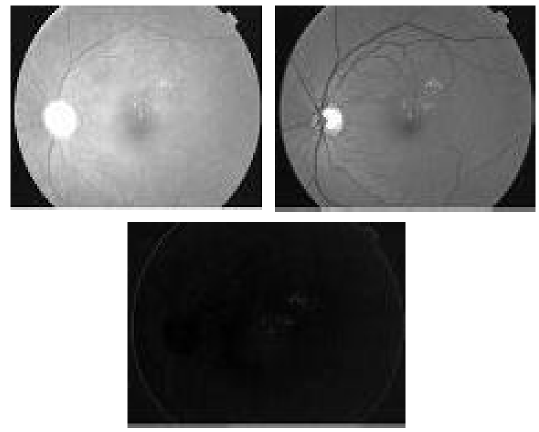

Fig. 1: (a) Red channel, (b) Green channel, (c) Blue channel

Filtering: Filtering is frequently utilized in image processing to smooth noise and to enhance or detect features within an image. An infinite number of filters, both linear and non-linear, are offered in image processing to improve the quality of the images. The core objective of image smoothing is to filter out the noise present in the image signal without compromising on the region of interest. Gaussian function for smoothing the noise-affected images is a big hit among the researchers. The effectiveness of the Gaussian function is directly proportional to different choices of the standard deviation (sigma) of the Gaussian filter. The impact of filters on the images can be commonly understood by their use that have pronounced regions of varying sizes to visualize the effect on edges or by the application of test patterns like sinusoidal sweeps to visualize the effects in the frequency domain. Gordon *et al*. (1992) has made clear that the Gaussian distribution in 2-D has the form:

$$G(\sigma) = \frac{1}{2\Pi}\frac{\exp(-x^2+y^2)}{2\sigma^2}$$

Where, σ is the standard deviation of the distribution. It is also assumed that the distribution has a mean of zero (i.e. it is centered about the line $x = 0$). The discovery of the blood vessels is accomplished by means of a steerable Gaussian filter and its orientation can be decided by the user. Furthermore, it has been reported in the literature that these filters can be quite successful for edge detection and image analysis. The local structure of an image can be portrayed in a stable and robust form by the output of Gaussian Separable Steerable filters. Cesar *et al*. (2003) has drafted that the Steerable filters are a class of filters, in which a filter of arbitrary orientation is synthesized as a linear combination of a set of basis filters. The result of applying the steerable filter is shown in Fig. 2 with $\theta = 190°C$.

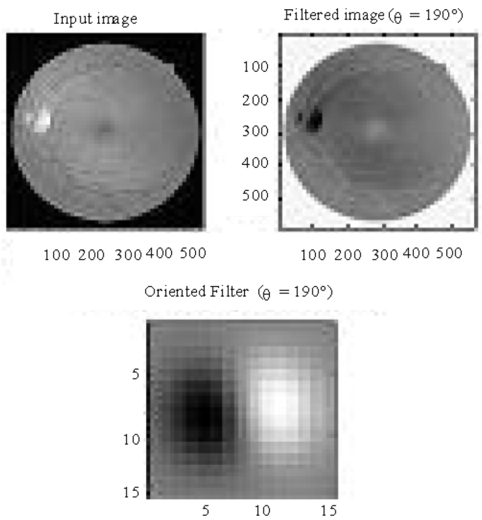

Fig. 2: The effect of steerable filter orientation

Curvature: Curvature is the change in direction for stable displacements along the curve. The intrinsic geometric property of a surface can be found out mathematically and the notion is referred as the Gaussian curvature of a surface, or even simply the curvature of a surface. Gaussian curvature is a mathematical quantity attached to an area of a surface. Surface curvature such as Gaussian, mean and principal curvatures extracted from an image whose intrinsic surface properties describing local shape have come in to play a crucial role in both characterizing and recognizing free-formed curved surface.

The most common approach in region segmentation is based on the signs of Gaussian and mean curvature resulting in four surface types namely convex (peak), concave (pit) and two types of saddle regions. Moreover, the significance of curvature at a point on the surface is also viewpoint invariant. Numerous researchers have succeeded on the problem of interpreting range data from curved surfaces, the major methods have totally relied on the segmentation with the help of mean and Gaussian curvature signs. Ernest *et al.* (1992), Freeman *et al.* (1991) and Lee *et al.* (1990) indicated that the first derivative denotes the intensity gradient and the second derivative signifies curvature characteristics. The Gaussian curvature K and the mean curvature H used for surface characterization are given in Eq. 1.

Gaussian curvature K and the mean curvature H

$$K = \frac{g_{uu}g_{vv} - g^2_{uv}}{(1+g^2_u+g^2_v)^2}$$

$$H = \frac{g_{uu}(1+g^2_v)+g_{vv}(1+g^2_u)-2g_u g_v g_{uv}}{2(\sqrt{(1+g^2_u+g^2_v)^3}}$$

Table 1: Surface interpretation of Gaussian curvature (k) and mean curvature (H) signs

	K >0	K=0	K<0
H<0	Peak	Ridge	Saddle ridge
H=0	None	Plane	Minimal surface
H>0	Pit	Valley	Saddle valley

These curvatures are viewpoint invariant under rigid transformation. Smooth surfaces are locally characterized by them and are classified into surface types using a combination of their sign (Table 1). The blood vessel detection is performed by convolving a Gaussian filter and this result in a high peak at the central location of the blood vessel.

The results produced by the application of the algorithm are shown in the Fig. 3. Figure 3a gives mean curvature based output and its equivalent binary curvature representation is shown in Fig. 3b. Figure 3c and d shows the blood vessel traced at the peak.

Optic disc detection: The optic disc is the basis and on top is the gateway of all the vessels and the optic nerve into the retina. It appears in color fundus images as a bright yellowish or white region. Its shape is likely more or less circular, interrupted by the outgoing vessels. Sometimes the shape may be an ellipse as a result of a non-negligible angle between the images and object planes. Canny's algorithm is applied only to the red channel owing to the reason that the blood vessels are absent in the red component region of the optic disc. Normally, the intensity is quite high in the optic disc region as opposed to the other regions of the image. Hence, this feature can be used to trace the optic disc in the retinal image. After locating the candidate region, edge finding part of the Canny's algorithm is applied to trace the boundaries of the optic disc.

Figure 4a represents the original image of the red channel and the resultant optic disc is shown in Fig. 4b. Figure 4c furnishes the template of Fig. 4a and d illustrate the effect of edge detection through Canny's algorithm.

Post processing: The output of the algorithm is a binary image and in that there may be some misclassified pixels which appeared as undesirable noise in the classified image. Therefore, it is obligatory to perform post-processing. Generally speaking, morphological operations can be quite handy to eliminate the small noise components. In order to completely fill the vessels, specific morphological operations like dilation and area close are used and are enlightened well by Cesar *et al.* (2003). Dilation is basically used where the object moves over the image and set the centre pixel to `1' if any of the neighboring 4 or 8 pixels are also a `1' otherwise set the

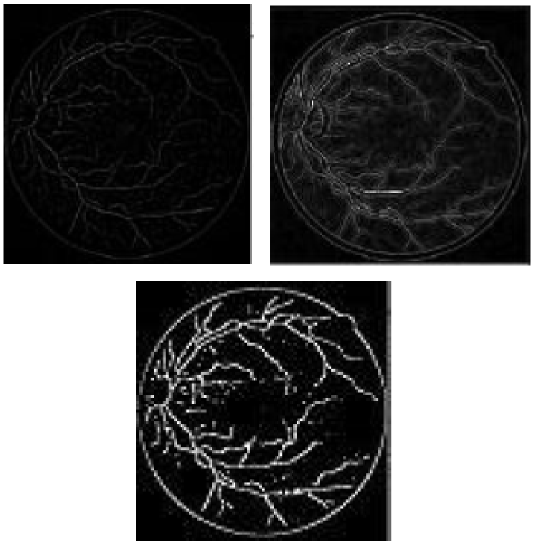

Fig. 3: (a) Mean curvature, (b) Binary curvature (c) Peak

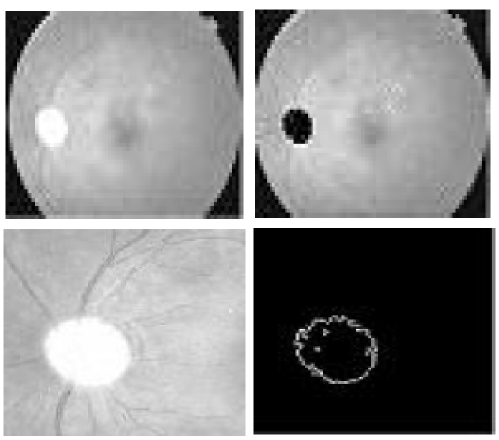

Fig. 4: (a) Red channel, (b) Optic disc localization, (c) Original template, (d) Template optic disc

centre pixel to `0'. When the object lies on the border of the set, the image set is set to `0'. Area closing smoothes but fuses areas together and eliminates holes in the image and are elucidated by Tickle *et al*. (2007).

Figure 5a furnish the peak representation Fig. 5b shows after eliminating the circle contour Fig. 5c Segmented vessel.

Since, the peak output produces a circle contour (Fig. 5a) around the blood vessel, it is required to eliminate the same for further processing. Pixel level elimination algorithm has been used to overcome such circumstances. The two level horizontal separations have been performed from either side till the first pixel has come across on the contour. The left behind pixels are alienated from both the sides by two level vertical eradication procedures (Fig. 5b).

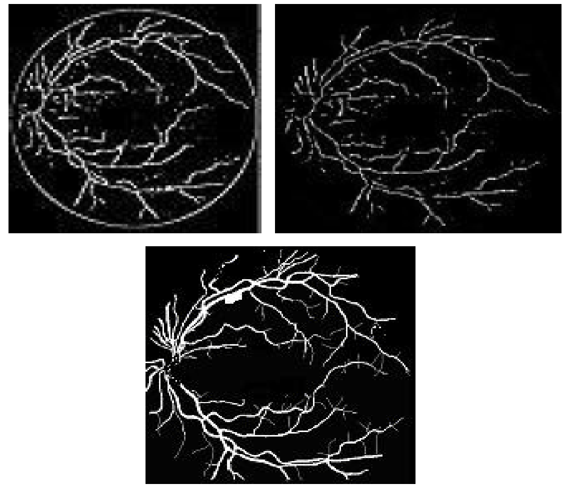

Fig. 5: (a) Peak, (b) Peak after post processing, (c) segmented image

The tracing of the blood vessel starts from around the optic disc and stops when no high peak is detected (Fig. 5c). A 4×4 window has been considered at each pixel point to take a assessment of the curve direction and proceeded till the last part of the peak has accomplished. After attaining the end of the peak the algorithm once again move toward to the optic disc for further processing. This algorithm produces output exactly in one pixel level; so the thinning routine is not essential which adds to the advantageous of to the algorithm. Thus time taken to take thin has reduced.

RESULTS

Lee *et al*. (2001) has investigated that the ocular fundus images can be acquired by using non-mydriatic cameras that do not require the dilation of the eyes through drops, or through angiograms applying fluorescein as a tracer. The projected algorithm has been tested and evaluated making use of the well acknowledged public database referred as DRIVE with 40 images that include 7 pathological images. These images are captured in digital form from a Canon CR5 non-mydriatic 3CCD camera at 45 Field of View (FOV), are of size 768×584 pixels and are available in compressed JPEG format. The database which stores the images and their equivalent representation of manually segmented blood vessels as standard templates has presented by Staal *et al*. (2004).

The robustness and the reliability of the suggested algorithm have been analyzed by considering 10 images from the DRIVE database. The output of the algorithm has been compared with its equivalent manual standard template version in the database. The intended

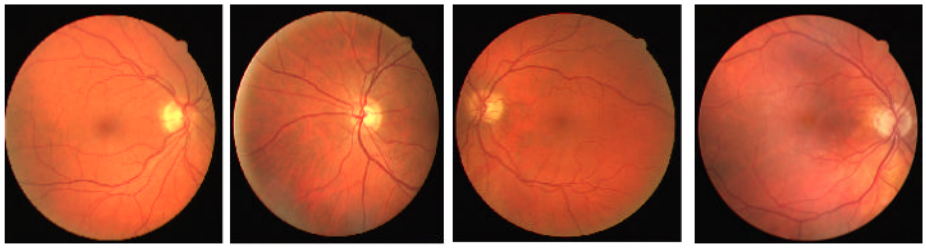

Fig. 6 (a): Input image

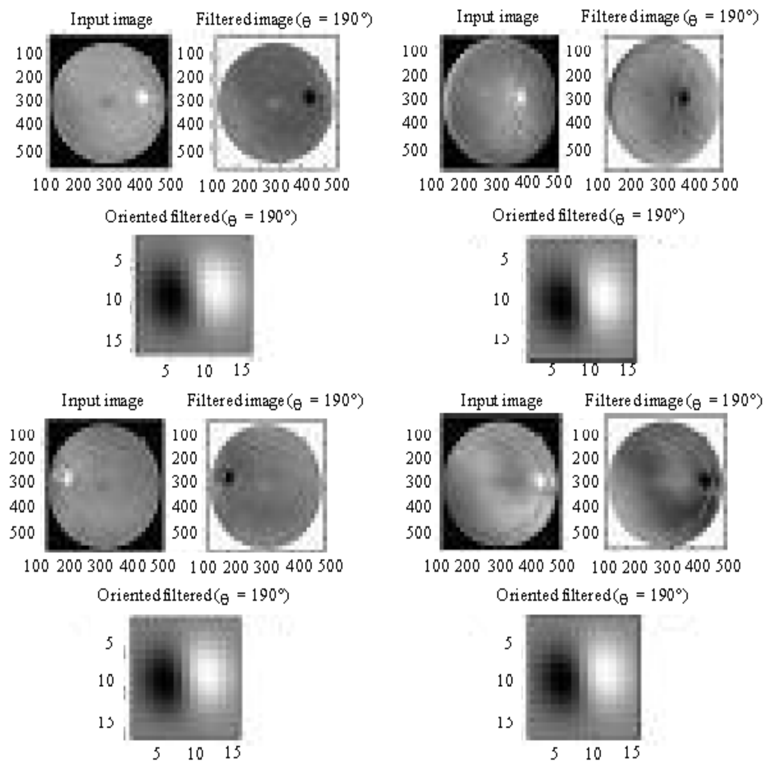

Fig. 6 (b): Filtering effect

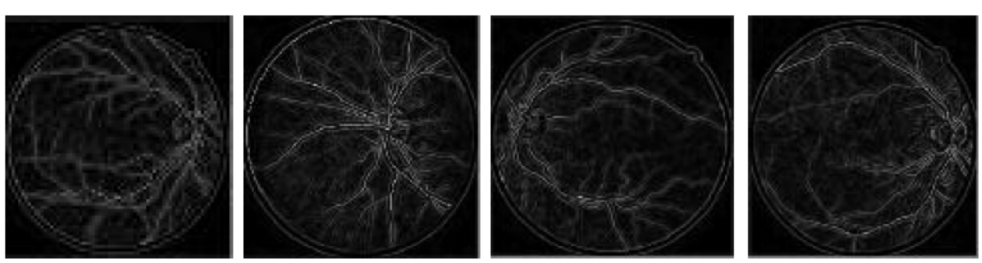

Fig. 6 (c): Binary curvature

algorithm has scored over its corresponding standard template version in respect of the clarity with reference to blood veins and small veins. Figure 5 displays the result obtained from the algorithm for 4 images of the same database. The first row Fig. 6a is the original image, the second row Fig. 6b provide the effect of Gaussian filtering, Fig. 6c third row the mean curvature, Fig. 6d and e fourth and fifth row furnish the peak representation and the last row Fig. 6f after post processing.

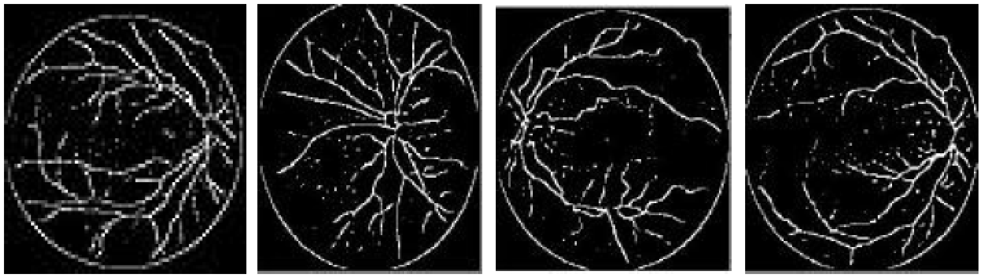

Fig. 6 (d): Peaks

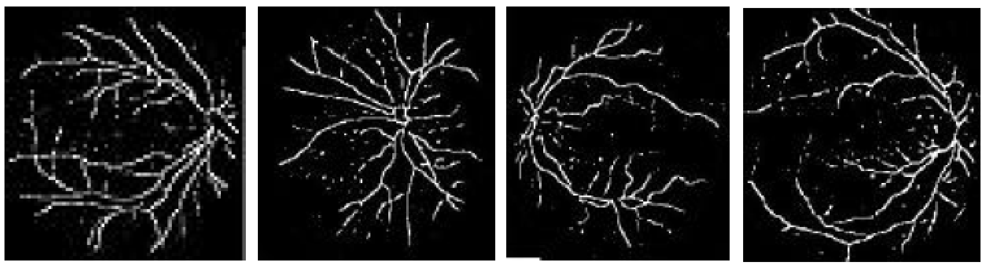

Fig. 6 (e): Peaks after removing the elliptical outline

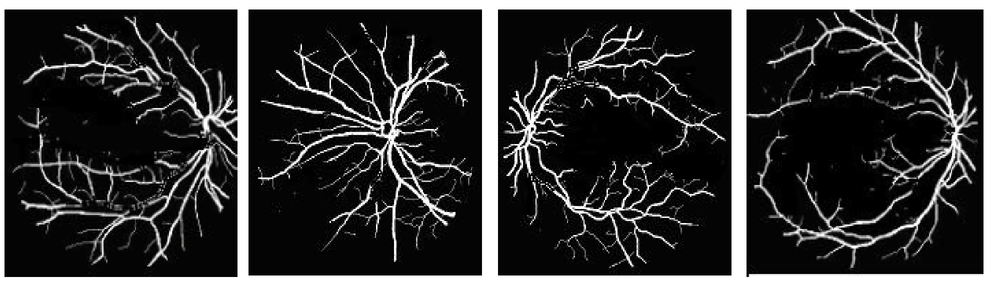

Fig. 6 (f): Blood vessel segmented image

CONCLUSION

To identify the region of interest for blood vessel classification, it is indispensable to locate the optic disc initially. A novel method has been tried out in this work primarily to locate the optic disc and tracking the vessel in the vicinity of the optic disc. The results produced are promising and express the applicability and efficiency of the projected technique. This algorithm is also capable of detecting any looping structure in the blood vessel which is a manifestation of abnormal symptom. The ultimate plan is to fabricate a complete retinal image analysis system that will assist and improve the screening of diabetic retinopathy.

REFERENCES

Akita, K. and H. Kuga, 1982. Pattern recognition of blood vessel networks in ocular fundus images. IEEE, pp: 436-441.

Akita, K. and H. Kuga, 1982. A computer method of understanding ocular fundus images. Pattern Recog., 15: 431-443.

Akita, K. and H. Kuga, 1981. A method of understanding blood vessel patterns in ocular fundus images. Trans. IECE. Japan J64-D, 8: 729-736.

Chaudhuri, S., S. Chatterjee, N. Katz, M. Nelson and M. Goldbaum, 1989. Detection of blood vessels in retinal images using two dimensional matched filters. IEEE. Trans. Med. Imaging, 8: 263-269.

Cesar, R.M. and H.F. Jelinek 2003. Segmentation of Retinal Fundus Vascular in Nonmydriatic Camera Image Using Wavelets. In Suri, J.S. and S. Laxminarayanan (Eds.). Angiography and plaque imaging. CRC Press, London, pp: 193-224.

Ernest, M. Sokely and Shang You and Wu, 1992. Surface Parameterization and Curvature measurement of Arbitary 3-D objects: Five Practical methods. IEEE. Trans. Pattern Anal. Machine Intelligence, 14: 8.

Freeman, W.T. and E.H. Adelson, 1991. The Design and Use of Steerable Filters. IEEE. Trans. Pattern Anal. Machine Intelligence, 13: 891-906.

Francis, K.H. Quek and W.I. Richard, Yarger and Cemil Kirbas, 2003. Surface Parameterization in Volumetric Images for Curvature-Based Feature Classification. IEEE. Trans. Sys. Man and Cybernetics-Part B: Cybermetics, 33: 5.

Gordon, G.G., 1992. Face Recognition Based on Depth and Curvature Feature. Proc. IEEE. Comput. Soc. Conf. CVPR., pp: 808-810.

Gordon, G.G., 1992. Application of Morphology to Feature Extraction for Face Recognition. Proceedings SPIE/SPSE Nonlinear Image Processing III, 1658.

Hoover, A., V. Kouznetsova and M. Goldbaum, 2000. Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response. IEEE. Trans. Med. Imaging, 19: 203-210.

Kanski, J.J., 1994. Clinical Ophthalmology. 3rd Edn. Butterworth.

Leandro, J.J.G., J.V.B. Soares, R.M. Cesar and H.F. Jelinek, 2003. Blood vessel segmentation of nonmydriatic images using wavelets and statistical classifiers. In: Proceedings of the Brazilian Conference on Computer Graphics, Image Processing and Vision (Sibgrapi03), Sao Paulo, Brazil. IEEE. Comput. Soc. Press, pp: 262-269.

Lee, S.J, C.A. McCarty, H.R. Taylor and J.E. Keeffe, 2001. Costs of mobile screening for diabetic retinopathy: A practical framework for rural populations. Aus. J. Rural Health, 8: 186-192.

Leandro, J.J.G., R.M. Cesar and H. Jelinek, 2001. Blood vessels segmentation in retina: Preliminary assessment of the mathematical morphology and of the wavelet transform techniques. In: Proceding of the 14th Brazilian Symposium on Computer Graphics and Image Processing. IEEE. Comput. Soc., pp: 84-90.

Lee, J. and E. Milios, 1990. Matchin Range Image of Human Faces. Proc. 3rd ICCV., pp: 722-726.

Michal Sofka, 2006. Retinal Vessel Centerline Extraction Using Multiscale Matched Filters, Confidence and Edge Measures. IEEE. Trans. Med. Imaging, 25: 1531.

Stephane Mallat and Sifen Zhong, 1992. Characterization of Signals from Multiscale Edges. IEEE. Trans. PAMI., 14: 710-732.

Sinthanayothin, C., J. Boyce and C.T. Williamson, 1999. Automated localisation of the optic disc, fovea and retinal blood vessels from digital colour fundus images. Br. J. Ophthalmol., 83: 902-912.

Staal, J.J., AM.D. Abramoff, M. Niemeijer, M.A. Viergever and B. Van Ginneken, 2004. Ridge-based vessel segmentation in color images of the retina. IEEE. Trans. Med. Imag., 23: 501-509.

Sato, Y., S. Nakajima, N. Shiraga, H. Atsumi, S. Yoshida, T. Koller, G. Gerig and R. Kikinis, 1998. Three-dimensional multi-scale line filter for segmentation and visualization of curvilinear structures in medical images. Med. Image Anal., 2: 143-168.

Tickle, A.J., J.S. Smith and Q.H. Wu, 2007. Development of Morphological Operators for Field Programmable Gate Arrays. Sensors and their Applications XIV (SENSORS07) IOP Publishing Journal of Physics: Conference Series 76 012028 doi:10.1088/1742-6596/76/1/012028.

Zheng Liu , Chutatape Opas and Shankar M. Krishnan, 1997. School of EEE, Nanyang Technological University. Singapore Automatic Image Analysis of Fundus Photograph Proceedings 19th International Conference IEEE/EMBS Chicago, ILUSA.