Blood vessel extraction of diabetic retinopathy using optimized enhanced images and matched filter

Asit Subudhi
Subhra Pattnaik
Sukanta Sabut

Blood vessel extraction of diabetic retinopathy using optimized enhanced images and matched filter

Asit Subudhi,^a Subhra Pattnaik,^a and Sukanta Sabut^{b,*}

^aSOA University, Department of Electronics and Communication Engineering, Institute of Technical Education and Research, Bhubaneswar, Odisha, India

^bSOA University, Department of Electronics and Instrumentation Engineering, Institute of Technical Education and Research, Bhubaneswar, Odisha, India

Abstract. Accurate extraction of structural changes in the blood vessels of the retina is an essential task in diagnosis of retinopathy. Matched filter (MF) technique is the effective way to extract blood vessels, but the effectiveness is reduced due to noisy images. The concept of MF and MF with first-order derivative of Gaussian (MF-FDOG) has been implemented for retina images of the DRIVE database. The optimized particle swarm optimization (PSO) algorithm is used for enhancing the images by edgels to improve the performance of filters. The vessels were detected by the response of thresholding to the MF, whereas the threshold is adjusted in response to the FDOG. The PSO-based enhanced MF response significantly improved the performances of filters to extract fine blood vessels structures. Experimental results show that the proposed method based on enhanced images improved the accuracy to 91.1%, which is higher than that of MF and MF-FDOG, respectively. The peak signal-to-noise ratio was also found to be higher with low mean square error values in enhanced MF response. The accuracy, sensitivity, and specificity values are significantly improved among MF, MF-FDOG, and PSO-enhanced images ($P < 0.05$). © 2016 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.3.4.044003](https://doi.org/10.1117/1.JMI.3.4.044003)]

Keywords: diabetic retinopathy; retinal image; blood vessels; matched filter; particle swarm optimization; accuracy.

Paper 16113R received Jun. 17, 2016; accepted for publication Nov. 4, 2016; published online Nov. 30, 2016.

1 Introduction

Retinal vascular disorders affect the blood vessels of the retina in diabetes. Around 65.1 million patients are affected by diabetes as estimated by the Indian Council of Medical Research, and by 2030, India will have 101.2 million diabetic people.¹ About 33% of patients with diabetes suffer from diabetic retinopathy, which affects the microvasculature of the retina and is the leading cause of blindness. The microstructural blood vessels of the retina are more prone to diabetic retinopathy. This leads to loss of vision due to damages of the small blood vessel of the retina.² New diabetic retinopathy cases could be monitored appropriately at the early stages to prevent blindness.³ An accurate detection of the artery-vein crossings and structural patterns of the blood vessels of the retina is an important task for diagnosis, evaluation, and clinical study.⁴

In most clinical scenarios, the structure of retinal blood vessels could be visualized directly in a noninvasive process with very high-resolution systems.⁵ The edge in an image provides useful information of the structural changes in an image and edge detection techniques are used to find the boundary region of the blood vessel structures.^{6,7} The two-dimensional (2-D) Gabor wavelet with classifier is used for automated segmentation of the vasculature in retinal images by classifying each image pixel as a vessel or nonvessel, based on the pixel's feature vector. A 2-D Gabor wavelet with adaptive thresholding achieves 0.96 of region of convergence (ROC) curve of on the DRIVE database.⁸ The fuzzy clustering classifier partitioned

the retinal images into four sections by the symmetric division of the optical disk to extract features from vessels to independent vessels. The matched filter (MF) method has the advantages of simplicity and effectiveness to detect vessels by filtering and thresholding the original images.⁹

The filtering-based methods are popular approaches to segment the vessels by maximizing the filter response to vessel-like structures.^{9,10} Mathematical morphology operators are also applied for segmenting the structure of retinal vessels. The automatic detection methods with Fuzzy C-means clustering are used to reconstruct the morphology by segmenting the coarse and fine structures on low-contrast retinal images. It achieved a sensitivity and specificity of 86% and 99%, respectively, by comparison with ground-truth images.¹¹ The global networks of blood vessels are traced by tracing out the center lines of the vessels after detecting the vessel edge.¹² Matched Gaussian and Kalman filters were used to detect and track blood vessels by locating the center point and width of a vessel.¹³ The center line extraction approach combining with MF has been found effective both qualitatively and quantitatively in automatic detection of vessel boundaries.¹⁴

Laplacian and Gaussian operators are used to detect the edge of the blood vessels. A morphological operator was used to extract only the blood vessel and then the edge of the blood vessels were clearly detected by a multiscale segmentation function which assists in detecting the retinal vessel structures.^{15–17} In a report, the matched filter with first-order derivative of Gaussian (MF-FDOG) method using the MF and the first-order-derivative

*Address all correspondence to: Sukanta Sabut, E-mail: sukanta207@gmail.com

of the Gaussian was found to be more accurate in distinguishing between the retinal vessels structures compared to MF alone.¹⁸

A new edge detection technique based on matched filtering and region growing used to detect retinal blood vessels was found to have a better accuracy than that presented by state-of-the-art approaches with an area under the ROC curve found to be 0.96.¹⁹ The blood vessels detected effectively with better peak-signal-to-noise ratio (PSNR) and with an accuracy of 96% using the curvelet transform with modified curvelet coefficients.²⁰ Complex continuous wavelets transform with adaptive histogram-based thresholding process used for multi-scale vessel enhancement for automatic vessels detection and the result shows higher accuracy (95%) and specificity (97%), respectively.²¹ In a report, the black top-hat transformation and double-ring filter were used to detect retinal blood vessels and linear discriminant analysis (LDA) was used for classifying the arteries and veins.²² The graph cut technique achieved excellent performance in segmenting blood vessels and the optic disk in the fundus retinal images in DRIVE data sets.²³ A hybrid method based on mathematical morphology and a fuzzy clustering algorithm was proven to be effective for extraction of vessels in the retinal image.²⁴

The improved versions of MF algorithm such as MF combined with pulse coupled neural networks,²⁵ improved MF response by Ant colony algorithm,²⁶ and genetic algorithm-based optimization²⁷ were used for image enhancement. The best gray level image enhancement is achieved according to the objective criterion by optimizing the parameters with the help of particle swarm optimization (PSO).²⁸ The optimal parameters of the multiscale Gaussian MF achieved better results in segmenting retinal vessels.²⁹ An automated method based on standard line operator and a modified line operator has been used successfully to detect new vessels in retinal images with a high accuracy.³⁰ In an automatic screening system, the best model parameter ($\sigma = 0.0104$) classified the normal and DR stages with an accuracy of 96.15 which could be used for faster diagnosis of diabetic retinopathy.³¹ In an integrated system, using a curvelet transform and tunable band-pass filter is found to be effective in enhancing vessel edges, whereas the fuzzy conditional entropy discriminates vessels widths efficiently.³² An MF based on kernel function with a Cauchy distribution method improved the accuracy in detecting the retinal vessel compared to other MF-based methods.³³

In this paper, we used PSO-based optimization techniques to enhance the edges of the gray-level image to improve the image quality of the MFs responses. The vascular structures of the retinal image have been extracted by the MF, MF-FDOG, and the MF with PSO-based enhanced images. The performance results were compared to the enhanced image by evaluating the quantitative parameters such as accuracy and sensitivity.

2 Method

To evaluate the vessel detection methodology, images are collected from a publicly available database, the DRIVE.³⁴ The DRIVE databases have been widely used for performance evaluation to test the proposed vessel segmentation methodologies as it provides manual segmentations. Ten retinal images are used from the DRIVE database and the parameters such as sensitivity and specificity results are compared with the gold standards of each image. The damages in blood vessels are identified for diabetic retinopathy cases using MF and MF-FDOG algorithms as per the flow diagram represented in Fig. 1. The appearance of blood vessels is strengthened by converting an RGB image into grayscale. Initially, the original image was scaled to enhance the contrast of the image, and filters were applied to detect blood vessels by using MATLAB 9.0. 2.1. Independent *t*-test was used to compare the MF and MF-FDOG results and also the percentage changes of the recorded images. The significance level α was set at 0.05 for all tests and the statistical analyses were performed with SPSS version 22 for Windows.

2.1 Preprocessing

In the preprocessing stage, the median filter is used to remove noise and artifacts to improve the quality of the raw image and increase its contrast. The images were resized before being processed to extract the vessel structures.

2.2 Retinal Vessel Extraction by Matched Filter

MF is a template matching algorithm¹⁸ that is used in the detection of the blood vessels in retinal images and other applications as well. The MF based on Gaussian kernel function is expressed as

Fig. 1 Flowchart of the proposed method for blood vessel extraction in DR images.

$$K(x, y) = -\exp(-x^2/2\sigma^2) \quad \forall |y| \leq \frac{L}{2}, \quad |x| \leq t.3, \quad (1)$$

and MF is defined as

$$f(x, y) = \left[\frac{-1}{\sqrt{2\pi}\sigma} \right] \times \exp\left(\frac{-x^2}{2\sigma^2}\right) - m \quad \forall |y| \leq \frac{L}{2}, \quad |x| \leq t.3, \quad (2)$$

$$m = \frac{\int_{-ts}^{ts} \frac{1}{\sqrt{2\pi}\sigma} \times \exp\left(\frac{-x^2}{2\sigma^2}\right) dx}{2ts}, \quad (3)$$

where L is the length of the vessel segment that has the same orientation and is used to smooth noise, σ defines the spread of the intensity profile. t is a constant and is usually set to 3.

The kernel, $k(x, y)$, is rotated to detect the vessels in different orientations with the maximum response of the filter bank. It is found that by rotating the kernel by 15-deg intervals, it is adequate to detect vessels with an acceptable amount of accuracy with 12 kernels.⁹ The values at $L = 9$ and $\sigma = 2$ are found to be the best parameter that gives the maximum response.⁹ A Gaussian curve has infinitely long double sided trails truncated at $u = \pm 3\sigma$. The N is defined as

$$N = \{(u, v), \forall u \leq 3\sigma, \forall v \leq L/2\}. \quad (4)$$

The corresponding weights in the kernel i ($i = 1, \dots, 12$ which is the number of kernels) are given by

$$k_i(x, y) = -\exp\left(\frac{-u^2}{2\sigma^2}\right) \quad \forall P_i \in N. \quad (5)$$

If A is a number of points in N , the mean value of kernel is computed as

$$m_i = \sum_{P_i \in N} k_i(x, y) / A. \quad (6)$$

Thus, the convolution mask is given by

$$k_i(x, y) = k_j(x, y) - m_i \quad \forall P_i \in N. \quad (7)$$

2.3 Retinal Vessel Extraction by MF-FDOG

The first derivative of Gaussian is an MF with zero-mean Gaussian filter used to detect both vessels and nonvessels.

The MF-FDOG method is an effective method in detecting fine vessels that are missed by the MF.¹⁹ The first-order derivative of the Gaussian (FDOG) is

$$G(x, y) = -x/\sqrt{2\pi}\sigma^3 \exp(-x^2/2\sigma^2). \quad (8)$$

In the MF-FDOG techniques, the signal response h and a threshold T is then applied to distinguish the vessels and nonvessel edges. The local mean of d is then calculated and denoted by d_m . The local mean value of an element of signal d_m is used to adjust the threshold to detect the true vessels and remove the nonvessel edges. If the magnitude in d_m is low, the threshold value will be small to detect the vessels and vice versa. Thus, high threshold T could be used to suppress the nonvessel edges. Two response images, H (by the MF) and D (by the FDOG), are obtained after filtering the retinal image with the MF-FDOG filter. The local mean image of D is calculated by filtering D with a mean filter given by $D_m = D * W$, where W is a $w \times w$ filter with elements are all $1/w^2$. The local mean image is normalized so that each element is within $[0, 1]$ and the normalized image is denoted by $\bar{D}_m$.

The threshold T is then set as $T = (1 + \bar{D}_m) \cdot T_C$, where T_C is the reference threshold and is defined as $T_C = C \cdot \mu_H$.

μ_H is the mean value of the response image H , and c is a constant, with values between 2 and 3. By applying T to h , the final vessel map M_H is obtained as

$$M_H = 1(x, y)T(x, y), \quad M_H = 0 H(x, y) < T(x, y).$$

2.4 PSO-Based Enhanced Image

The contrasts between blood vessels are very low; therefore, image enhancement is the main task of this work. The images are enhanced by PSO techniques to improve the performance of match filters to extract blood vessels. The PSO is an optimization technique in which the particles fly through the problem space by following a personal and global best. A transformation function generates a new intensity by taking the intensity value of each pixel from the input image value to produce an enhanced image. In the proposed work, the quality of the enhanced image is evaluated automatically using these functions. In Swarm intelligence-based optimization algorithm, the fitness value of every particle depends on the problem.³⁵ The algorithm operates iteration by iteration and the output of each iteration is compared with local best and global best. The global best solution of

Fig. 2 (a) Original test image, (b) gray-scaled image, and (c) ground truth image from DRIVE database.

a particle (g_{best}) is computed with swarm and the local best of a particle (p_{best}) is computed by itself. The position and velocities of particles are updated in each iteration and repeated until they meet some convergence criterion.

2.4.1 Transformation function

A transform function is used in spatial domain to generate a new intensity value for each pixel of the original image. The enhancement process is denoted by $g(i, j) = T[f(i, j)]$, where $f(i, j)$ is the gray value of the (i, j) 'th pixel of the input image, $g(i, j)$ is the gray value of the (i, j) 'th pixel of the enhanced image, and T is the transform function. A less time consuming local enhancement method applies transformation on a pixel considering intensity distribution among its neighboring pixels.³⁵ It takes both global and local information to produce the enhanced image. Local information is extracted from a user defined window of size $n \times n$. The transformation T is defined as

$$g(i, j) = K(i, j)[f(i, j) - c \times m(i, j)] + m(i, j)^a, \quad (9)$$

where a and c are two parameters, $m(i, j)$ is the local mean of the (i, j) 'th pixel of the input image over a $n \times n$ window, and $k(i, j)$ is the enhancement function which takes both local and global information. The local mean and enhancement function are defined as

$$m(i, j) = \frac{1}{n \times n} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} f(x, y).$$

One form of the enhancement function $k(i, j)$ used in this work is

$$K(i, j) = \frac{K.D}{\sigma(i, j) + b},$$

where K and b are parameters, D is the global mean, and $\sigma(i, j)$ is the local standard deviation of (i, j) 'th pixel of the input image over a $n \times n$ window, which is defined as

$$D = \frac{1}{M * N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j),$$

$$\sigma(i, j) = \sqrt{\frac{1}{n \times n} \sum_{x=0}^n \sum_{y=0}^n [f(x, y) - m(i, j)]^2}. \quad (10)$$

The transformation function is defined as

$$g(i, j) = \frac{k.D}{\sigma(i, j) + b} [f(i, j) - c \times m(i, j)] + m(i, j)^a. \quad (11)$$

The contrast of the image is stretched considering the local mean as the center of stretch by using the above equation. All the parameters a, b, c, k produce large variations in the processed image.

2.4.2 Evaluation criteria

An objective function is used to evaluate the quality of the enhanced image. It is formed by combining performance measures such as entropy value, sum of edge intensities, and number

of edgels (edge pixels).³³ The objective function considered here is

$$F(I_e) = \log\{\log[E(I_s)]\} \times \frac{n_{\text{edgels}}(I_s)}{M \times N} \times H(I_e), \quad (12)$$

where I_e is the enhanced image produced by the transformation function. The Sobel operator used to detect edgels. An automatic threshold detector produces an edge image (I_s) on the enhanced image. The n_{edgels} is the number of pixels, whose intensity value is above a threshold in the Sobel edge image. The entropy value is calculated on the enhanced image as

$$H(I_e) = - \sum_{i=0}^{255} e_i,$$

where $e_i = h_i \log_2(h_i)$ if $h_i \neq 0$, otherwise $e_i = 0$, and h_i is the probability of occurrence of i 'th intensity value of enhanced image.

2.5 Evaluation Parameter

To compute the sensitivity, specificity, precision, accuracy, and false positive rate (FPR) of this method, four quantities named true positive (TP), false positive, false negative (FN), and true negative (TN) were used. TP is used to represent the vessel pixels properly detected as vessel pixels. FPR is the number of nonvessel pixels wrongly detected as vessel pixels. FN is the number of vessel pixels wrongly detected and TN is the number of nonvessel pixels properly detected as nonvessel pixels.

The performance of the proposed algorithm is evaluated in terms sensitivity, specificity, precision, FPR, and accuracy, which are computed with the following equations:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100,$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100,$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100,$$

$$\text{FPR} = (1 - \text{specificity}) \times 100,$$

$$\text{Accuracy(Acc)} = \frac{TP + TN}{TP + FP + TN + FN} \times 100.$$

The PSNR is used to evaluate the intensity changes of an image between the original affected image and the output images.

The PSNR can be computed as

$$\text{PSNR} = 10 \log_{10}(2^n - 1) / \text{MSE}, \quad (13)$$

and the mean square error (MSE) is given by

$$\text{MSE} = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n |I_a(i, j) - I_o(i, j)|^2. \quad (14)$$

3 Results and Discussions

We implemented the proposed method of improved MF based on an enhanced image by the PSO algorithm and the performance was evaluated with MF and MF-FDOG filters with

optimized MF. Figure 2 represents one of the original images taken from DRIVE database. The DRIVE database consists of forty images, which are divided into a training set and a test set by the authors of the database. The DRIVE database has its own gold standard image which is used to evaluate the extracted parameters. The corresponding gold standard image has been used for observing the performance results and obtaining different evaluated parameters. Figures 3(b) and 4(b) shows the extracted blood vessels of the retinal images by applying filters at threshold 0.4.

The retinal images taken from DRIVE database and preprocessed to extract vessel structures with better accuracy according to the flow diagram are presented in Fig. 1. The MF and MF-FDOG algorithms were implemented on the affected DR images [Figs. 2(a) and 2(b)], and the result is shown in Figs. 3(a) and 3(b). Similarly, the PSO-enhanced MF output images are shown in Fig. 4(c). The accuracy, sensitivity, specificity, precision, and FPR of the image have been evaluated w.r.t. ground truth image Fig. 2(c). The PSNR and MSE parameters were calculated between the gray-scale images.

Tables 1–3 represent the simulation results of the evaluation parameters of ten images for MF, MF-FDOG, and PSO-based MF calculated at a threshold of 0.4 because we got the best segmented image at the mentioned threshold. Table 1 presents the evaluated parameters, i.e., accuracy, sensitivity, specificity, precision, and FPR for all 10 images by MF, Table 2 presents the results for MF-FDOG and Table 3 represents for the mean values for the PSO + MF method. The comparative results of the three methods are summarized in Table 4, which shows that

Fig. 3 (a) Output image of MF and (b) extracted output of MF-FDOG.

Fig. 4 (a) Gray-scaled image of enhanced image and (b) output image of proposed method (PSO-enhanced MF).

Table 1 Evaluated parameters of MF.

Image no.	Accuracy	Sensitivity	Specificity	Precision	FPR
1	0.8897	0.2509	0.9558	0.3697	0.0442
2	0.8788	0.2493	0.9541	0.3939	0.0459
3	0.8803	0.1143	0.9688	0.2975	0.0312
4	0.8988	0.1021	0.9839	0.4041	0.0161
5	0.8856	0.1967	0.9619	0.3640	0.0381
6	0.8730	0.0285	0.9705	0.1003	0.0295
7	0.8935	0.2202	0.9644	0.3940	0.0356
8	0.8533	0.0965	0.9329	0.1316	0.0671
9	0.8875	0.0955	0.9615	0.1881	0.0385
10	0.8958	0.4000	0.9438	0.4081	0.0562
Mean	0.88363	0.1754	0.95976	0.30513	0.04024

Table 2 Evaluation of parameters of MF-FDOG for DRIVE database.

Image no.	Accuracy	Sensitivity	Specificity	Precision	FPR
1	0.8864	0.2092	0.9556	0.3248	0.0444
2	0.8905	0.2599	0.9651	0.4681	0.0349
3	0.8850	0.0554	0.9803	0.2438	0.0197
4	0.8963	0.1641	0.9736	0.3967	0.0264
5	0.8912	0.2270	0.9624	0.3925	0.0376
6	0.8868	0.1091	0.9746	0.3266	0.0254
7	0.8972	0.1025	0.9803	0.3520	0.0197
8	0.8933	0.1872	0.9622	0.3259	0.0378
9	0.8992	0.0793	0.9747	0.2235	0.0253
10	0.8974	0.2702	0.9562	0.3670	0.0438
Mean	0.89233	0.16639	0.9685	0.34209	0.0315

the accuracy of the PSO-based MF is 91.1%, which is higher compared to MF and MF-FDOG accuracies of 88.36% and 89.74%, respectively. The accuracy, sensitivity, and specificity improved significantly between MF, MF-FDOG, and PSO-based MF results ($P < 0.05$). The high PSNR with low MSE values has been obtained in PSO-based MF compared to MF and MF-FDOG operators as represented in Table 5.

3.1 Discussion

The blood vessels in DR images are extracted by using many methods. In the proposed work, the images are preprocessed initially to increase the contrast and also to enhance the image for the accurate vessels' extraction. The PSO technique is used to enhance the edgels of images and the MF is used to extract the

Table 3 Evaluated parameters of proposed PSO-enhanced MF.

Image no.	Accuracy	Sensitivity	Specificity	Precision	FPR
1	0.9099	0.4226	0.9602	0.5235	0.0398
2	0.9045	0.2426	0.9837	0.6403	0.0163
3	0.9014	0.3675	0.9631	0.5352	0.0369
4	0.9098	0.2322	0.9823	0.5831	0.0177
5	0.9172	0.3811	0.9766	0.6430	0.0234
6	0.8944	0.3368	0.9588	0.9588	0.0412
7	0.9183	0.3425	0.9790	0.6315	0.0210
8	0.9102	0.3210	0.9686	0.5025	0.0314
9	0.9198	0.4505	0.9636	0.5366	0.0364
10	0.9250	0.3548	0.9802	0.6342	0.0198
Mean	0.91105	0.34516	0.97161	0.61887	0.02839

Table 4 Comparative results of evaluated parameters.

Operator	Accuracy	Sensitivity	Specificity	Precision	FPR
MF	0.884	0.175	0.959	0.305	0.0402
MF-FDOG	0.892	0.166	0.969	0.342	0.032
PSO + MF	0.911	0.345	0.972	0.619	0.028

Table 5 Comparative results of PSNR and MSE values.

Filters	PSNR	MSE
MF	58.17	0.095
MF-FDOG	58.33	0.093
PSO + MF	59.35	0.071

vessel structure. It was observed that compared to the original image the enhanced image has more edgels with a higher intensity. The subjective evaluations were performed on the resulting enhanced image which says about the effectiveness of PSO. The results of MF, MF-FDOG, and enhanced MF have been compared in retinal images of the DRIVE database. The accuracy, sensitivity, specificity, precision, and FPR are used for finding the performance of the filters. The mean accuracy of the enhanced based MF is found to be higher compared to the MF and MF-FDOG responses. A higher accuracy of 91.11% was found when compared to the MF and MF-FDOG accuracies of 88.3% and 89.2%, respectively. Significant improvement was found among MF, MF-FDOG, and PSO-enhanced images in all the evaluated parameters. The resulting PSO-based enhanced images with MF are found to be better with high PSNR and low MSE values compared to only match filter responses.

4 Conclusions and Future Work

Automated assessment of diabetic retinopathy based on computerized segmentation of blood vessels of retinal image provides the tool for an ophthalmologist to detect diabetic retinopathy. In this paper, the retinal blood vessels have been extracted in the collected images from the DRIVE database by the MF, MF-FDOG, and MF on enhanced image-based PSO. MF with a single scale does not provide an acceptable performance since the widths of the vessels are varying across the image. The PSO-based parameter selection is employed in this work for enhancing the edges of the images. The approach is tested on affected images to show the advantages over existing approaches. An accuracy of 91.2% and specificity of 97.2% are found in enhanced based images with MF methods. The comparative result shows that the enhanced based MF operator outperforms the MF and MF-FDOG methods in terms of accuracy, sensitivity with higher PSNR, and less error. The major drawback of the proposed method is the visibility of the blood vessel to detect very small vessels, connectivity of vessels, and the lower accuracy of the test results. In order to improve these factors, isolated vessels can be connected to the main vessels which will be investigated in our future work.

Disclosures

No conflicts of interest, financial or otherwise, are declared by the authors.

References

1. H. King, R. E. Aubert, and W. H. Herman, "Global burden of diabetes, 1995-2025 prevalence, numerical estimates and projection," *Diabetes Care* **21**(9), 1414-1431 (1998).
2. R. N. Frank, "Diabetic retinopathy," *N. Engl. J. Med.* **350**(1), 48-58 (2004).
3. S. J. Lee et al., "Costs of mobile screening for diabetic retinopathy: a practical framework for rural populations," *Aust. J. Rural Health.* **9**(4), 186-192 (2001).
4. G. Dougherty, "Image analysis in medical imaging: recent advances in selected example," *Biomed. Imaging Interv. J.* **6**(3), 1-9 (2010).
5. V. S. Hari, V. P. Jagathy, and R. Gopikakumari, "Quadratic filter for the enhancement of edges in retinal images for the efficient detection and localization of diabetic retinopathy," *Pattern Anal. Appl.* 1-21 (2015).
6. S. Sarangi, D. Majhi, and S. K. Sabut, "Evaluation and comparison of retinal vessels extraction using edge detectors in diabetic retinopathy," *Int. J. Signal Imaging Systems Engineering* **9**(3), 174-183 (2016).
7. J. B. Soares et al., "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," *IEEE Trans. Med. Imaging* **3**(9), 1214-1222 (2006).
8. E. Grisan and A. Ruggeri, "A divide et impera strategy for automated classification of retinal vessels into arteries and veins," in *Proc. 25th Int. Conf. IEEE Engineering in Medicine and Biology Society*, Vol. 1, pp. 890-893 (2003).
9. S. Chaudhuri et al., "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Trans. Med. Imaging* **8**(3), 263-269 (1989).
10. Y. Tolia and S. Panas, "A fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering," *IEEE Trans. Med. Imaging.* **17**(2), 263-273 (1998).
11. M. M. Fraz, M. Y. Javed, and A. Basit, "Evaluation of retinal vessel segmentation methodologies based on combination of vessel centerlines and morphological processing," in *Proc. Int. Conf. on Emerging Technologies*, pp. 232-236 (2008).
12. O. Chutatape, L. Zheng, and S. M. Krishnan, "Retinal blood vessel detection and tracking by matched Gaussian and Kalman filters," *Proc. Int. Conf. IEEE Eng. Med. Biol. Soc.* **20**, 3144-3149 (2008).

13. M. Sofka and C. V. Stewart, "Retinal vessel centerline extraction using multiscale matched filters, confidence and edge measures," *IEEE Trans. Med. Imaging* **3**(12), 1531–1546 (2006).
14. V. V. Kumari and N. Suriyanarayanan, "Blood vessel extraction using Wiener filter and morphological operation," *Int. J. Comput. Sci. Emerg. Technol.* **1**(4), 7–11 (2010).
15. Y. Wang and S. C. Lee, "A fast method for automated detection of blood vessels in retinal images," in *Conf. Record of the 31st Asilomar Conf. on Signals, Systems & Computers*, pp. 1700–1704 (1998).
16. E. Moghimirad, S. H. Rezaatofighi, and H. Soltanian-Zadeh, "Retinal vessel segmentation using a multi-scale medialness functions," *Comput. Biol. Med.* **42**(1), 50–60 (2012).
17. M. Al-Rawi, M. Qutaishat, and M. Arrar, "An improved matched filter for blood vessel detection of digital retinal images," *Comput. Biol. Med.* **37**(2) 262–267 (2007).
18. M. Nandy and M. Banerjee, "Retinal vessel segmentation using Gabor filter and artificial neural network," in *Proc. Int. Conf. Emerging Applications of Information Technology*, Kolkata, pp. 157–160 (2012).
19. B. Zhang, L. Zhang, and F. Karray, "Retinal vessel extraction by matched filter with first-order derivative of Gaussian," *Comput. Bio. Med.* **40**(4), 438–445 (2010).
20. K. Jeyasri, P. Subathra, and K. Annaram, "Detection of retinal blood vessels for disease diagnosis," *Int. J. Adv. Res. Comput. Sci. Software Eng.* **3**(3), 6–12 (2013).
21. A. Fathi, A. Reza, and N. Nilchi, "Automatic wavelet-based retinal blood vessels segmentation and vessel diameter estimation," *Biomed. Signal Proc. Control.* **8**(1), 71–80 (2013).
22. C. Muramatsu et al., "Automated detection and classification of major retinal vessels for determination of diameter ratio of arteries and veins," *Proc. SPIE* **7624**, 76240J (2010).
23. A. Salazar-Gonzalez et al., "Segmentation of the blood vessels and optic disk in retinal images," *IEEE J. Biomed. Health Inf.* **18**(6), 1874–1886 (2014).
24. M. H. Fadzil et al., "Extraction and reconstruction of retinal vasculature," *J. Med. Eng. Tech.* **31**(6), 435–442 (2007).
25. C. Yao and H. J. Chen, "Automated retinal blood vessels segmentation based on simplified PCNN & fast 2D-OTSU algorithm," *J. Central South. Univ. Technol.* **16**(4), 640–646 (2009).
26. M. Cinsdikici and D. Aydin, "Detection of blood vessels in ophthalmoscope images using MF/ant (matched filter/ant colony) algorithm," *Comput. Methods. Prog. Biomed.* **96**(2), 85–95 (2009).
27. M. Al-Rawi and K. Huda, "Genetic algorithm matched filter optimization for automated detection of blood vessels from digital retinal images," *Comput. Methods Prog. Biomed.* **87**(3), 248–253 (2007).
28. A. Gorai and A. Ghosh, "Gray-level image enhancement by particle swarm optimization," in *World Congress on Nature & Biologically Inspired Computing*, pp. 72–77 (2009).
29. K. S. Sreejini and V. K. Govindan, "Improved multiscale matched filter for retina vessel segmentation using PSO algorithm," *Egypt. Inf. J.* **16**(3), 253–260 (2015).
30. R. A. Welikala et al., "Automated detection of proliferative diabetic retinopathy using a modified line operator and dual classification," *Comput. Methods Prog. Biomed.* **114**(3), 247–261 (2014).
31. M. K. Mookiah et al., "Evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: a hybrid feature extraction approach," *Knowledge-Based Syst.* **39**, 9–22 (2013).
32. S. S. Kar and S. P. Maity, "Retinal blood vessel extraction using tunable band-pass filter and fuzzy conditional entropy," *Comput. Methods Prog. Biomed.* **133**, 111–132 (2016).
33. H. Zolfagharnasab and A. R. Naghsh-Nilchi, "Cauchy based matched filter for retinal vessels detection," *J. Med. Signals Sens.* **4**(1), 1–9 (2014).
34. J. Staal and M. D. Abramoff, "Ridge-based vessel segmentation in color images of the retina," *IEEE Trans. Med. Imaging* **23**(4), 501–509 (2004).
35. K. James and E. Russell, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Networks*, pp. 1942–1948 (1995).

Asit Subudhi received his B.Tech degree in electronics and telecommunication engineering in 2005 and M.Tech degree in communication system engineering in 2010 from BPUT, Odisha, India. He is an assistant professor at the Department of Electronics and Communication Engineering, ITER, SOA University, Odisha, India. He has more than 10 years of experience in teaching and research. He has published research papers in journals and conferences. His research interest includes signal and image processing.

Subhra Pattnaik received her BE degree in electronics and communication from BPUT, Odisha, in 2012. She is a postgraduate student in digital signal and image processing at the Department of Electronics and Communication Engineering, ITER, Bhubaneswar. Her research interest is image processing and signal processing.

Sukanta Sabut received his diploma in rehabilitation engineering, BE in electronics and communication, MTech degree in biomedical instrumentation, and PhD in medical science and technology, IIT Kharagpur in 2010. He is an associate professor in electronics and instrumentation engineering, Faculty of Engineering, SOA University, Odisha, India. His research interest includes biomedical instrumentation signal and image processing. He has published research papers in international journals and conferences. He is a member of IEEE and IET.