Segmentation of Vessels in Fundus Images using Spatially Weighted Fuzzy c-Means Clustering Algorithm

Giri Babu Kande†, T.Satya Savithri††, and P.V.Subbaiah†††

† Department of Electronics & Communication Engineering, S.R.K. Institute of Technology, Vijayawada, India
†† Department of Electronics & Communication Engineering, Jawaharlal Nehru Technological University, Hyderabad, India
††† Department of Electronics & Communication Engineering, Amrita Sai institute of Science & Technology, Paritala, India.

Summary
This paper presents an algorithm for the extraction of Blood Vessels from Fundus images using Matched filter and Thresholding based on Spatially Weighted Fuzzy c-Means (SWFCM) clustering algorithm. Such a tool should prove useful to eyecare specialists for purposes of patient screening, treatment, and clinical study. We make use of a set of linear filters sensitive to vessels of different orientation and thickness. Such filters are obtained as linear combinations of properly shifted Gaussian kernels. The Spatially Weighted Fuzzy c-Means clustering algorithm is formulated by incorporating the spatial neighborhood information into the standard FCM clustering algorithm. An experimental evaluation demonstrates superior performance over global thresholding and a vessel detection methods recently reported in the literature. Due to its simplicity and general nature, our proposed algorithm is expected to be applicable to a variety of other applications.
Key words:
fundus, fuzzy c-means, matched filter, retina, vessel detection.

1. Introduction

Ocular fundus image assessment has been widely used by the medical community for diagnosing vascular and non vascular pathology. Inspection of the retinal vasculature may reveal hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke [1]. For example, central retinal artery occlusion usually causes generalized constriction of retinal arteries, while central retinal vein occlusion typically produces dilated tortuous veins, arteriosclerosis can cause arteries to acquire a copper or silver color. Hypertension may result in focal constriction of retinal arteries, and diabetes can generate new blood vessels (neovascularization). Among the features in ocular fundus image, the structure of retinal blood vessels plays an important role in revealing the state of diseases [1]. In addition, blood vessels can also serve as landmarks for image-guided laser treatment of choroidal neovascularization. Thus, reliable methods of vessel detection that preserve various vessel measurements are needed.

Diabetic retinopathy (DR) is a vascular disorder affecting the microvasculature of the retina. It is emerging as one of the important causes of blindness in both developing and developed countries. The World Health Organization (WHO) has estimated that, the number of adults with diabetes in the world would increase alarmingly: from 135million in 1995 to 300 million in 2025. In India, this increase is expected to be the greatest; nearly 195% from 18 million in 1995 to 54 million in 2025. The most effective treatment is early detection through regular screenings. During the screenings, color retinal images are obtained using fundus camera. However, this results in a large number of fundus images being produced that require manual analysis and diagnosis. In other words, medical professionals have to spend a great deal of time and energy to review these photographs. It would be more cost effective if the initial task of analyzing the retinal photographs can be automated so that only the abnormal retinal images need to be reviewed by the medical professionals.

On the other hand, diabetic retinopathy resulting from long-term diabetes mellitus is one of the common diseases that lead to choroidal neovascularization (CNV). CNV is an important condition that leads to blindness. It decreases the amount of blood supplying the retina especially within the central area of acute vision [2]. One treatment strategy is the use of lasers to photocoagulate the affected areas of the retina. To obtain satisfactory results, the physician must identify the full extent of CNV and cauterize it completely [2]. Care must be taken to avoid radiating the macula (the area of acute vision), optic disc, and major blood vessels [3].

The organization of this paper is as follows. Section II describes the brief survey of existing literature. Section III describes the materials used for the proposed algorithm. In Section IV we propose a new algorithm to efficiently locate and extract blood vessels in ocular fundus images. The proposed algorithm is composed of four steps, Preprocessing, Matched filtering, Thresholding based on Spatially Weighted Fuzzy c-Means (SWFCM) clustering algorithm and Label filtering. The results are presented in Section V. Conclusions are in Section VI.

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2. Related Work

Several Studies have been conducted in the area of blood vessel extraction from retinal images. The edges in an image provide useful structural information about object boundaries. The edge detection algorithms based solely on the intensity at a given point in an image. They use standard image processing techniques such as the Canny, Sobel and Laplacian operators to extract lines within the image. While they are appropriate for many applications in computer vision, generic edge detection operators are less appropriate for the task of retinal vessel segmentation due to the fact that most vessels have boundaries that are blurred or indistinct, and very fine vessels are often only two or three pixels wide, which are not picked up, instead being seen as part of the background. In addition to this, the edge detection operations do not distinguish between vasculature and pathologies within the eye. This makes them unsuited to direct vessel extraction, however the Sobel operator is used to refine the results of the adaptive localized thresholding approach used by [4]. In [5] custom-made templates are used which resemble Prewitt operators to detect vessel boundaries and guide their exploratory algorithm. All the exploratory algorithms require some form of guidance, and a form of edge detection can provide one way of guiding the tracing of the vessel, so edge detection can play a part in an effective method of image segmentation despite the fact that in isolation they are not adequate for the entire task at hand.

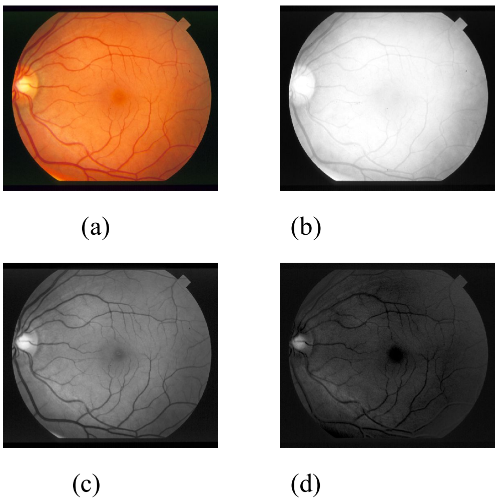
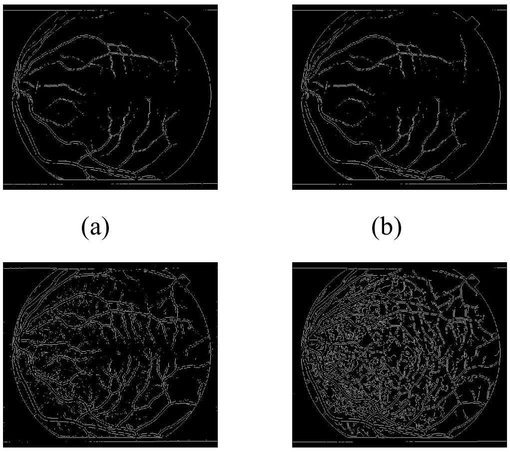


Fig. 1. (a) A typical color retinal image. (b) Red component image (c) Green component image (d) Blue component image.

Exploratory algorithms [5],[6] begin by sampling a large number of points within the image at regular intervals. They then perform operations on these sampled points to determine the likelihood that these pixels are within a blood vessel. Once some candidate seed points have been determined to be blood vessels, directional edge detection filters [5] are used to trace out the path of the blood vessel across the surface of the retina. Having acquired some candidate points that are likely to be vessels, antiparallel edges are searched for using directional templates similar to the edge detection templates of Sobel and Prewitt. Antiparallel edges are those that are in opposing directions on either side of the candidate vessel, of sufficient strength to indicate the presence of a legitimate edge. Once strong directional edges are detected, they must be filtered to determine the actual location of the blood vessel relative to the edges. Part of the filtering of the detected edges is that they are oriented at 180 degrees, ±22.5 degrees, in the case of [5]. This prevents edges that clearly belong to different vessels being grouped together as only those edges sufficiently parallel belong to the same vessel are recorded as being potential edges to the section of vessel being traced. This has the advantage of substantially reducing the processing required relative to pixel-based methods, as in the initial stage only some small number or pixels need be processed to determine whether or not they are likely to be vessel, and from this starting point only vessel pixels and a small boundary around them are processed. Pixels that represent vessels in an image consist of between 10% and 15% of the field of view, as given in [11][14] and verified in the course of our experiments. Because of this, exploratory algorithms can significantly cut down on the processing required per image. This is particularly relevant where vessel identification is being used to guide computer-controlled surgical equipment, as new images are typically provided to be processed at 30 or more frames per second from video equipment, and processing must be done in real time to provide feedback and guidance to surgical tools.

Recently some studies performed Ridge detection based on the observation that the vessels can be modelled as ridges, where for each pixel gradient is determined based on the intensity of that pixel and surrounding pixels. Once a gradient is determined for each pixel the direction of maximum curvature can be determined along a line covering several pixels, and the peak of the ridge is that point at which the gradient is zero. Once the ridges have been highlighted further processing is done to link ridges and classifies pixels based on their gradients and that of neighbouring vessel pixels. The effectiveness of one implementation of such an approach is shown in [14]. In this study the method was shown to perform fairly well, achieving a false positive rate of 1.9%, but a corresponding true positive rate of only 69.7%.

The use of mathematical morphology for segmentation of blood vessels is explained in [18]. The results obtained in [18] are compared against other current image segmentation techniques implemented in [8].The morphological approach of [8] could extract fine details more reliably than the wavelet approach that they used, but both approaches required post-processing with region-growing, Sobel edge detection or adaptive thresholding is used to produce the final image. Even following this processing the resulting outputs suffered from noise due to pathologies within the eye and an inability to pick up on very fine capillaries; however the work done by [18] was one of the better-performing techniques tested by [11].



(c) (d)
Fig. 2. Edge detection algorithms applied to green image of Fig. 1.(c): (a) Sobel edge detector, (b) Prewitt edge detector, (c) LOG edge detector, (d) Canny edge detector..

3. Materials

The proposed algorithm was tested and evaluated on STARE [10] database. The STARE database consists of 20 digitized slides captured by a TopCon TRV-50 fundus camera at 35° FOV. For two reasons we have chosen this database for performance evaluation. First, the retinal images have all hand labeled vessel segmentation and support quantitative evaluation in an objective manner. Second, the image set contains both normal and abnormal (pathological) cases. In contrast, most of the methods known from the literature have only been demonstrated upon normal vessel appearances, which are easier to discern. The 20 images were digitized from retinal fundus slides and are of 605 X 700 pixels, 24 bits per pixel (standard RGB). We only use the green band of the images.

4. Proposed Algorithm

The proposed approach is composed of four steps. Since blood vessels usually have lower reflectance compared with the background, a green component of retinal image will be separated. It was preprocessed to reduce the noise. Then we applied the matched filter to enhance blood vessels. The Spatially Weighted Fuzzy c-Means (SWFCM) clustering algorithm is used to distinguish between vessel segments and the background in the Matched filter response (MFR) image. A label filtering technique is used to remove the misclassified pixels.

4.1. Preprocessing

In order to reduce the distortions due to media decay (e.g. astigmatic blur, defocusing, color shift, uneven magnification, scratches, dust) the image of fig.1.c. was preprocessed by a 5x5 mean filter. The preprocessed image is shown in fig.3.(a)

4.2. Matched filter

It has been observed that the blood vessels in retinal images have the following three important properties which are useful for vessels analysis [12]:

1. The blood vessels usually have small curvatures and may be approximated by piecewise linear segments.
2. The vessels have lower reflectance compared to other retinal surfaces. They appear darker relative to the background. It is observed that these vessels almost never have ideal step edges. Although the intensity profile varies by a small amount from vessel to vessel, it may be approximated by a Gaussian curve

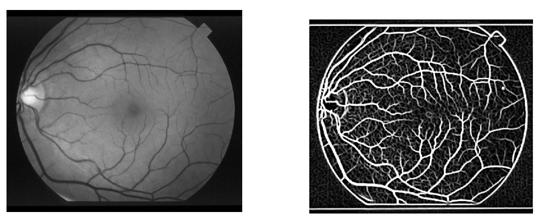
$$f(x,y) = A\{1 - k\exp(-\frac{d^2}{2\sigma^2})\}, \qquad (1)$$

where d is the perpendicular distance between the point *(x, y)* and the straight line passing through the center of the blood vessel in a direction along its length, σ defines the spread of the intensity profile, A is the gray-level intensity of the local background and k is a measure of reflectance of the blood vessel relative to its neighborhood.
3. The width of a vessel decreases as it travels radially outward from the optic disk and such a change in vessel caliber is a gradual one. Therefore, a vessel is defined as a dark pattern with Gaussian-shape cross-section profile, piecewise connected, and locally linear.

Because of the above-mentioned assumptions, instead of matching a single intensity profile of the vessels cross section, a significant improvement can be achieved by matching number of cross sections of identical profile simultaneously. Thus, a kernel can be used whose mathematical expression is

$$k(x,y) = -\exp(-\frac{x^2}{2\sigma^2}) \text{ for } |y| \le L/2. \qquad (2)$$

where L is the length of the segment for which the vessel is assumed to have a fixed orientation. Here the direction of the vessel is assumed to be aligned along the y-axis. Because a vessel may be oriented at any angles, the kernel needs to be rotated for all possible angles. A set of twelve 16x15 pixel kernels are applied by convolving to a fundus image and at each pixel only the maximum of their responses is retained.



(a) (b)
Fig.3. (a)Image after Preprocessing (b)Matched filtering result

4.3. Spatially Weighted Fuzzy c-Means Clustering algorithm

In order to properly extract the enhanced segments in the matched filter response (MFR) images, an effective thresholding scheme is necessary. Because some MFR images have complicated relationships or overlap between foreground and background, thresholding based on Spatially Weighted Fuzzy c-Means (SWFCM) clustering algorithm [9] is implemented.

The spatially weighted fuzzy c-means (SWFCM) clustering algorithm is formulated by incorporating the spatial neighboring information into the FCM algorithm. The weight in the algorithm, inspired by k-nearest neighbor (k-NN) pattern classifier by considering the neighborhood influence on the central pixel, is then modified to improve the performance of image thresholding. Since the gray level histogram of image is used instead of the whole data of image to calculate the parameter for the FCM algorithm, the method is as fast as the conventional techniques. Due to the consideration of the neighborhood information, the method is also noise resistant.

The Fuzzy C-means (FCM) algorithm is an iterative clustering method that produces an optimal c partition, which minimizes the weighted within group sum of squared error objective function $J_q(U,V)$:

$$J_q(U,V)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^q d^2(x_k,v_1) \qquad (3)$$

where $X=\{x_1,x_2,...,x_n\}\subseteq R^p$, n is the number of data items, c is the number of clusters with $2\le c<n, u_{ik}$ is the degree of membership of x_k in the i^{th} cluster, q is a weight exponent on each fuzzy membership, v_i is the prototype of the centre of cluster i, $d^2(x_k,v_i)$ is a distance measure between object x_k and cluster center v_i. A solution of the object function J_q can be obtained via an iterative process, which is carried as follows:

1)Set value for c, q and ε

2)Initialize the fuzzy partition matrix U.

3)Set the loop counter $b=0$.

4)Calculate the c cluster centers $\{v_i^{(b)}\}$ with $U^{(b)}$:

$$v_i^{(b)}=\frac{\sum_{k=1}^{n}\left(u_{ik}^{(b)}\right)^q x_k}{\sum_{k=1}^{n}\left(u_{ik}^{(b)}\right)^q} \qquad (4)$$

5)Calculate the membership $U^{(b+1)}.For\ k=1\ to\ n$, calculate the following :

$$I_k=\{i \mid 1\le i\le c, d_{ik}=\|x_k-v_i\|=0\},$$

$$\bar{I}_k=\{1,2,...,c\}-I_k;$$

for the k^{th} column of the matrix, compute new membership values :

a) if $I_k=\phi$, then

$$u_{ik}^{(b+1)}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(q-1)}} \qquad (5)$$

b) else $u_{ik}^{(b+1)}$ =0 for all $i\in\bar{I}_k$ $and \sum_{i\in I_k} u_{ik}^{(b+1)}=1; next\,k.$

6)If $\|U^{(b)}-U^{(b+1)}\|<\varepsilon$, stop; otherwise, set b=b+1 and go to step 4.

Since FCM algorithm is an iterative operation, it is very time consuming which makes the algorithm impractical used in image segmentation. To cope with this problems, the gray level histogram of image is applied to the algorithm. Define the non-negative integrate set $G=\{L\min, L\min+1,..., L\max\}$ as gray level, where L min is the minimum gray level, L max is the maximum gray level , so the grayscale is L max – L min. For image size S X T, at point (s,t), f(s,t) is the gray value with $0\le s\le S-1, 0\le t\le T-1$. Let *His* (g) denote the number of pixels having gray level g, g ∈ G. The statistical histogram function is as follows :

$$His(g)=\sum_{s=0}^{S-1}\sum_{t=0}^{T-1}\delta(f(s,t)-g) \qquad (6)$$

where g = {L min, L min+1,…, L max}, δ(0) =1 and δ (g ≠0) = 0. With the gray level histogram the membership function is still by (5), while the cluster centers are updated by:

$$v_i^{(b)}=\frac{\sum_{g=L_{\min}}^{L_{\max}}\left(u_{ig}^{(b)}\right)^q His(g)g}{\sum_{g=L_{\min}}^{L_{\max}}\left(u_{ig}^{(b)}\right)^q His(g)} \qquad (7)$$

It is important to note that k in (5) now denotes the gray level as g. Since the FCM algorithm now only operates on the histogram of the image, it is faster than the conventional version which processes the whole data.

The general principal of the techniques presented in this paper is to incorporate the neighborhood information into the FCM algorithm. Since in the standard FCM algorithm for a pixel $x_k \in I$ where I is the image, the clustering of x_k with class i only depends on the membership value $u_{ik,}$ if we consider a noisy image, since clustering process is related only to gray levels independently on pixels, FCM is noise sensitive. Considering the influence of the neighboring pixels on the central pixel, the fuzzy membership function given in (5) can be extended to

$$u_{ik}^{*} = u_{ik} P_{ik} \tag{8}$$

where $k = 1,2,...,n,n$ is the index of each pixel, and p_{ik} is the probability of data point k belonging to cluster i, referred to as weight in this paper which can be determined by the following neighborhood model. Therefore the degrees of membership u_{ik}^{*} and the cluster centers v_i are now updated via :

$$u_{ik}^{*(b)} = \frac{p_{ik}}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(q-1)}} \tag{9}$$

$$v_i^{(b+1)} = \frac{\sum_{k=1}^{n} \left(u_{ik}^{*(b)} \right)^{q} x_k}{\sum_{k=1}^{n} \left(u_{ik}^{*(b)} \right)^{q}} \tag{10}$$

The core idea now is to define the auxiliary weight variable p_{ik}, which is a priori information to guide the outcome of the clustering process. This paper proposes a method for determining the weight based on the neighborhood information inspired from k-nearest neighbor (k-NN) algorithm.

$$p_{ik} = \frac{\sum_{x_n \in N_k^i} 1 / d^2(x_n, k)}{\sum_{x_n \in N_k} 1 / d^2(x_n, k)} \tag{11}$$

where N_k is the data set of the nearest neighbors of central pixel k, and N_k^i is the subset of N_k composed of the data belonging to class i which is got after defuzzyfying the result fo the FCM algorithm in our method. In order to given an appropriate method to describe the probability of a data point belonging to any cluster, two improved implementations of the k-NN algorithm are introduced. First, the equation (11) is extended by considering the potential function of each feature vector .

$$K(x, x_k) = \frac{1}{1 + \alpha \| x - x_k \|^2} \tag{12}$$

where α is a positive constant, and $\| x - x_k \|^2$ is the norm of the vector $(x - x_k)$. Then the potential is modified by assigning the proximity of feature vector to each prototype instead of the potential for feature vector to feature vector. Hence the new equation for the weight value is defined as :

$$P_{ik} = \frac{\sum_{x_n \in N_k^1} 1 / 1 + a.d^2(x_n, v_i)}{\sum_{x_n \in N_k} 1 / 1 + a.d^2(x_n, v_i)} \tag{13}$$

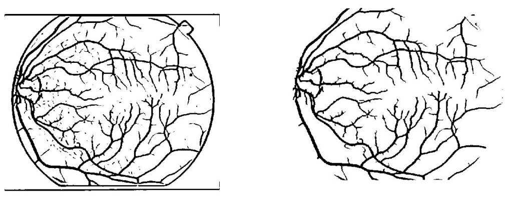
Where v_i is the prototype of cluster i. After the a- priori weight is determined, a new iteration step starts with this auxiliary variable p_{ik}. To prevent that the SWFCM gets trapped in a local minima, the SWFCM algorithm is initialized with the above fast FCM algorithm. Once the FCM is stopped, the SWFCM algorithm continues with the values for the prototypes and membership values obtained from the fast FCM algorithm. when the algorithm has converged, a defuzzification process then takes place in order to convert the fuzzy partition matrix *U* to a crisp partition. A number of methods have been developed to defuzzify the partition matrix *U,* in which the maximum membership procedure is the most important. The procedure assigns object k to the class C with the highest membership.

$$C_k = \arg_i \{ \max(u_{ik}) \},\ i = 1,2,...,c. \tag{14}$$

With this procedure, the fuzzy images are then converted to crisp image. For image thresholding, $c = 2$ in equation (14).

5. Label filtering

Connected component labeling is a simple image analysis technique that scans an image pixel-by-pixel and groups its pixels into components based on pixel connectivity. Here, we use this technique to identify individual objects in each thresholded image. The Label filtering tries to isolate the individual objects by using the eight-connected neighborhood and label propagation [15].



(a) (b)

Fig. 4. (a) Result of SWFCM (b)Label filtering result

6. Experimental Results

In this section, the results of the proposed algorithm are presented. In order to evaluate the performance, we compare our simulation results with the state-of-the-art results obtained from Piecewise threshold probing [10], Local Entropy thresholding [20], well-known Otsu thresholding and hand-labeled groundtruth

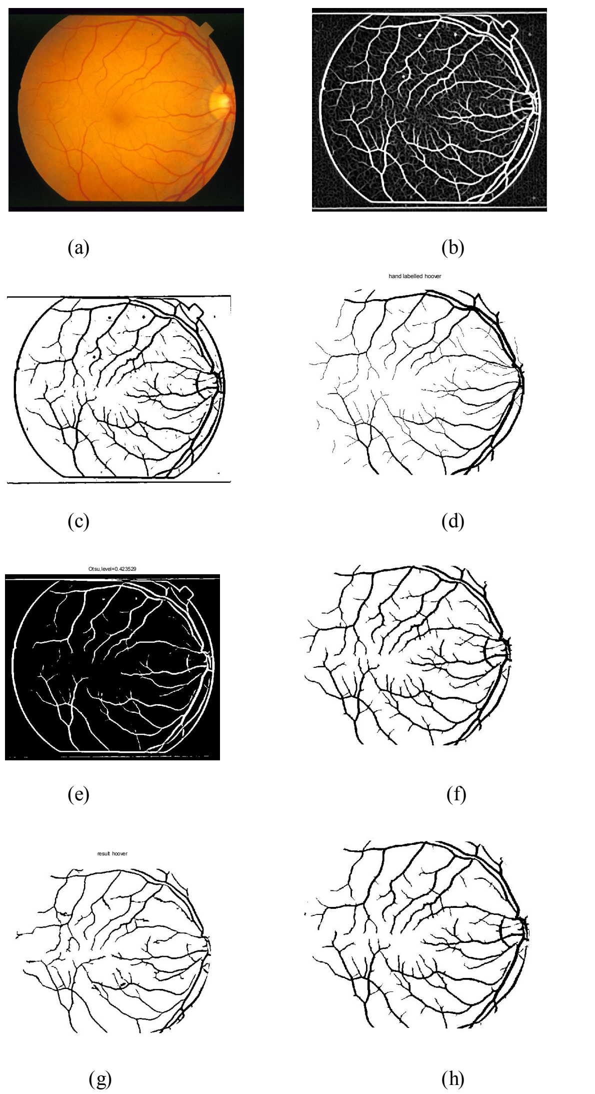


Fig.5 Comparison of results of normal color retinal image : (a) A typical color retinal image (b) enhanced blood vessels with 2-D Gaussian matched filter, (c)Result of SWFCM (d)Hand labeled vessel network by A. Hoover (e) Result from Otsu thresholding [16] (f) vessel network [20] (g) Result from [10] (h)binary blood vessel tree by our proposed approach.

segmentations. The algorithm is coded in MATLAB version 7.4 and is run on a 1.7GHz Core 2 Duo personal computer with a memory of 512MB. We use the same set of twenty 605 x 700 pixel retinal images (24bpp), as used in [10], [20]. The computational time for the whole process of the proposed algorithm takes approximately one minute for each retinal image.

Among the 20 images of STARE Database, 10 are of patients with no pathology (normals) and the other 10 contain pathology that obscures or confuses the blood vessel appearance in varying positions of the image (abnormals). Vessel detection results of normal, obscure and abnormal retinal images are shown in Figs. 5, 6 and 7.

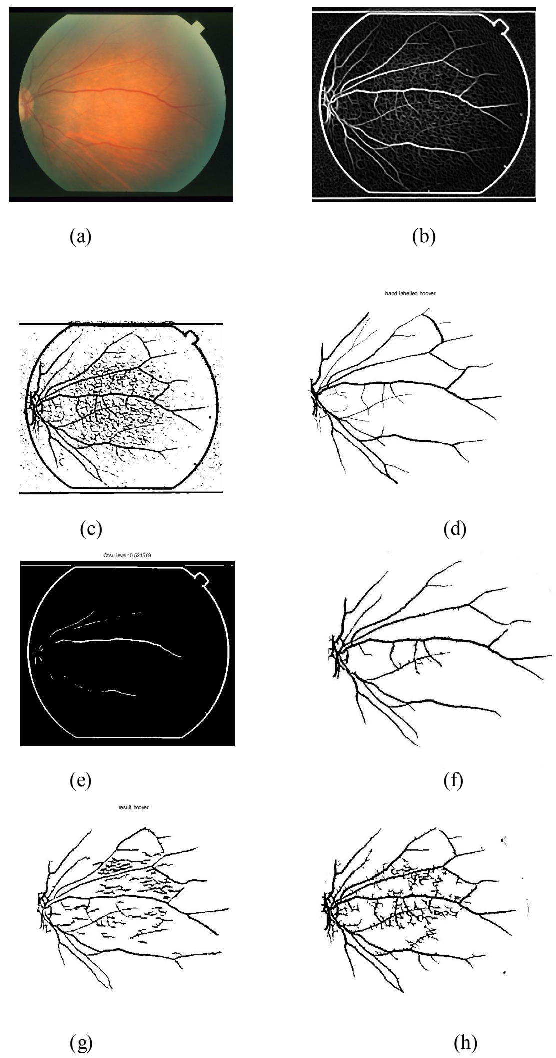


Fig.6. Comparison of results of obscure color retinal image : (a) A typical color retinal image (b) enhanced blood vessels with 2-D Gaussian matched filter, (c)Result of SWFCM (d)Hand labeled vessel network by A. Hoover (e) Result from Otsu thresholding [16] (f) vessel network [20] (g) Result from [10] (h)binary blood vessel tree by our proposed approach.

In the first example, a normal fundus image as shown in fig. 5. (a) is considered. Fig. 5 (h) shows the result of proposed method. The hand-labeled groundtruth segmentation is shown in Fig. 5 (d). The results of Otsu's method, Local Entropy thresholding [20] and Piecewise threshold probing [10] are displayed in Figs. 5 (e),(f) and (g) respectively. Although, algorithms in [10], [20] perform very well, a significant improvement is achieved by the proposed algorithm for normal retinal images. The proposed approach performs very well in extracting blood vessels.

The test image in the second example is the obscure fundus image as shown in fig. 6. (a). The results of thresholding by applying the different algorithms to the retinal image appear in Figs. 6 (e)-(g). The smaller blood vessels are not extracted well in [20] and Otsu's method.

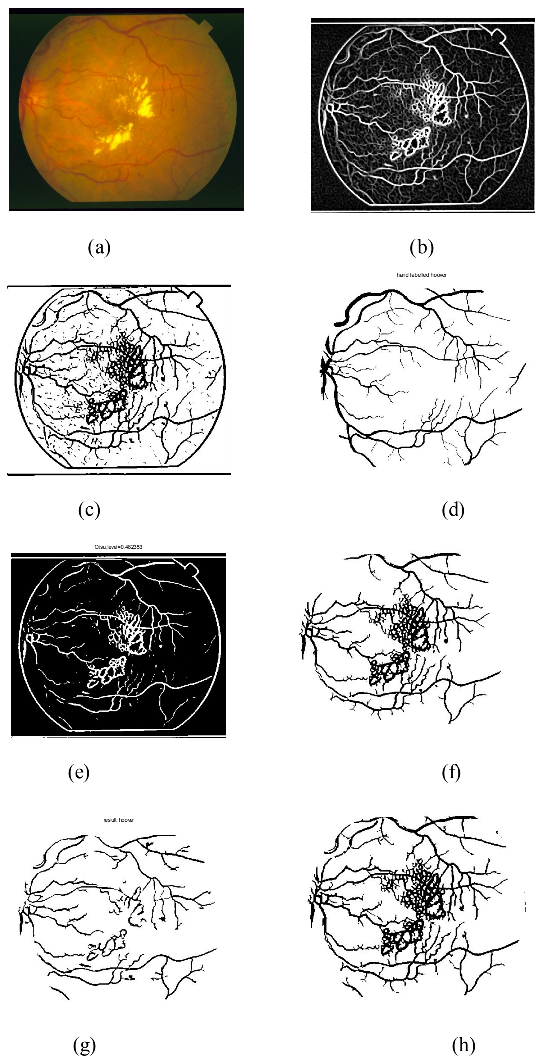


Fig.7. Comparison of results of abnormal color retinal image : (a) A typical color retinal image (b) enhanced blood vessels with 2-D Gaussian matched filter, (c)Result of SWFCM (d)Hand labeled vessel network by A. Hoover (e) Result from Otsu thresholding [16] (f) vessel network [20] (g) Result from [10] (h)binary blood vessel tree by our proposed approach.

The proposed method performs best by segmenting even the smaller blood vessels compared to other methods.

The performance on abnormal retinal image is shown in fig. 7. It can be seen in Fig 7 (h) that when compared with results of [10], [20] and Otsu Thresholding (Figs. 7 (e), (f), and (g)), the proposed method segments the blood vessels very well from the background. But the major obstacle in our approach is the presence of lesions in the abnormals. Our algorithm is sensitive to lesions because their boundaries partially match the shape of matched filter kernels, while the algorithm in [10] is more robust to lesions.

7. Conclusions

In this paper, a novel spatially weighted fuzzy c-means (SWFCM) clustering algorithm for vessel detection in ocular fundus images is presented. The method not only takes into account of the advantage of the fuzzy framework, but also considers the spatial relation among pixels. The weight plays a key role in this algorithm, which is derived from k-NN algorithm and is modified to improve the property in the SWFCM algorithm. The performance of the proposed method is compared with the with the state-of-the-art Piecewise threshold probing [10], Local Entropy thresholding [20] and well-known Otsu thresholding. The proposed method retains the computational simplicity, and at the same time, can achieve accurate segmentation results in the case of normal retinal images and images with obscure blood vessel appearance. In the case of abnormal retinal images with lesions, some lesions are also misdetected in addition to blood vessels. Since the algorithm is initialized with fast FCM algorithm, the presented approach is as fast as the conventional techniques. Also, owing to the incorporation of spatial information, the proposed algorithm is less prone to noise. Our future work aims at applying the shape analysis and classification strategies to the segmented vessels produced by method described in this work. Because of its simplicity and general nature the proposed algorithm is expected to be applicable to a variety of other applications.

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Giri Babu Kande received B.Tech in Electronics & Communication engineering from Nagarjuna University, Guntur, India in 1996 and M.E in Electronic Instrumentation from Andhra University, Visakhapatnam, India in 2000. He is working as professor, Departmentment of Electronics & Communication Engineering, S.R.K.Institute of Technology, Vijayawada, India. He published 5 papers in various journals and conferences. He is the Life member of ISTE. His research interests include Signal processing, Image Processing and Neural Networks.

Dr.T.Satya Savithri received B.Tech in Electronics & Communication engineering from N.I.T, Warangal, and M.E in Microwave and Radar Engg from Osmania University, India and PhD from Jawaharlal Nehru Technological university, Hyderabad, India. She is working as Associate Professor in Electronics & Communication engineering in the same university. She published 9 papers at national / international journals and conferences. She is the Life member of IE and ISTE. Her research interests include Signal processing and Image Processing.

Dr.P.Venkata Subbaiah obtained his B.E degree in ECE from Bangalore university in1980. He secured ME degree from Andhra University in 1983. JNTU, Hyderabad has conferred PhD degree for his work on Micro Antenna Test Facilities in 1995. He produced three Ph Ds so far under JNTU, Hyderabad. His areas of interest include Microwave Antennas, communicative and Instrumentation. He published 45 papers at national / international journals and conferences. He is the recipient of Sir Thomas ward memorial prize from the Institute of Engineers (India) in 1989-90. Currently he is the Principal, Amrita Sai Institute of Science & Technology, Paritala, Krishna Dist, Andhra Pradesh, India.