Retinal Image Segmentation by using Texture-based Gabor Filter Optimized by Gradient Descent Followed by Evolutionary Algorithm

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ABSTRACT
Segmentation and localization of fundus image is a crucial step of pathologies in diagnosing the retinal diseases. Swelling in different parts of vasculature, as change in width along blood vessels and tortuosity may lead to eye-blindness. This process can be utilized in automated screening of the patients suffering from diabetic retinopathy**.** An attempt was made to apply texture based Gabor filter which captures the band-pass filter bank characteristics of the eye and its output was used to detect the discontinuities and derive statistical properties helping in segmenting and classifying retinal images. This work deals with a general problem of segmentation of multi-texture images using clustering of Gabor filter output features, required to be separated in order to get better classification efficiency. Therefore, an effort was done to formalize it as an objective function for tuning filter parameters with Gradient descent and Genetic Algorithm. The results showed both quantitative and qualitative segmentation results of retinal images with improved classification accuracy.

Keywords
Retinal fundus images, blood vessels segmentation, Genetic Algorithm, Diabetic Retinopathy**,** Gabor Filter, Gaussian Post Filter.

1. INTRODUCTION
Segmentation is an important step which is required in many image processing applications to extract useful information. In medical imaging field, segmentation is required to identify the disease embedded in particular organ, e.g. it helps in early diagnosis of diseases like glaucoma, diabetic retinopathy and macular degeneration by segmenting retinal images [1-3]. Glaucoma is one of the most common diseases and if it is not early detected, may have serious cost, can even lead to eye blindness. Most of the existing detection and assessment methods of diabetic retinopathy are manual, costly affair and also require trained ophthalmologists [4-5].

Morphological feature of retinal blood vessel may be utilized as a vital sign for various retinal diseases such as diabetes, arteriosclerosis and hypertension.

The geometrical changes in veins and arteries of the retinal images can be measured and applied to a variety of clinical studies to develop automatic diagnostic system for early detection of diseases [6]. Segmentation of retinal blood vessels suffers from two kinds of problems, one is the presence of a wide variety of vessel widths and the other is heterogeneous retinal background [7].

The analysis of retinal image based on computer-aided techniques, plays a key role in diagnostic procedures. However, automatic retinal segmentation process suffers from various drawbacks, i.e. the retinal images are often poorly contrasted, noisy and also the widths of retinal vessels may vary from very large scale to very small value. Therefore, in this work the images were preprocessed using adaptive thresholding and contrast enhancement techniques. Detection and assessment of blood vessels has been the area of research in medical imaging for the past few years. This work includes some algorithms that usually use some kind of vessel enhancement before applying segmentation techniques. The current methods producing high accuracy for retinal image with thick vessels requires high computational cost. The use of proposed methods in this work makes it possible to detect these vessels faster, while preserving a high accuracy.

This work proposed a texture based segmentation method inspired from texture based segmentation capabilities of human beings. Following this an attempt was made to formulate a mathematical model of the human beings' eye, leading discovery of the band-pass filter-bank characteristics of the eye. The transfer function used by these filters is formulated by the Gabor elementary functions. The outputs produced by Gabor filters applied on differently textured images are significantly distinct for the differently textured regions. Utilizing the discontinuities present in the outputs of filters used and their statistical properties obtained from mathematical formulation help in segmentation and classification of a given image. Previous works were done on designing and modeling Gabor filters to obtain the maximum discrimination of different textured regions present [8-9]. Most of the previous work done on designing Gabor filters were based on incorporation of such decision theoretic framework which in turn minimize the probability of misclassification for bi-partite images having two different textured regions [10]. However, the approach proposed in this work mainly deals with a more general problem of classifying multi-textured images by applying clustering on output features obtained from above-mentioned filters. This followed the concept of getting better classification results, which inherently requires moving the clusters far apart from each other. In this work, this concept was utilized in formulating as an objective function to design the Gabor filter by tuning its parameters using evolutionary genetic algorithms. It has been observed that genetic algorithms are very efficient in various optimization problems which are convolved with discontinuous and non-differentiable objective functions. This work proposed a model to implement a filter bank using Gabor filters and a classification scheme to get an efficient segmentation and classification results for differently textured images.

The word texture can be described by characteristics of surface and appearance of an object given by the shape, size, component composition, density, arrangement and proportion of its elementary parts. The human visual system has the ability to pre attentively segment out different textured regions in an efficient manner. Motivated from this realization, owing to already existing concept and by extensive study on this has lead to utilize promising theory of human texture perception. This human texture based concept is also supported by many psycho physical and Neuro-physiological data, which has shown that some form of analysis based on local spatial frequency is performed by human visual system by utilizing a bank of tuned band pass filters. Earlier, many years back this concept of local spatial frequency was already discussed by Gabor in the context of communication systems. In classical concept, an image is considered as either a collection of pixels in spatial domain and in frequency domain, it is expressed as sum of sinusoids of infinite extent. However it was observed by Gabor that the both representations, spatial and frequency based belong to opposite extremes in a joint space-spatial frequency representation. Frequency representation is viewed as a local phenomenon (i.e., as a local frequency) and its value may vary along with position throughout the varying textured-image. Utilizing the above paradigm under the human vision framework, the significant texture differences observed perceptually, are most-likely correspond to the differences present in the form of local spatial frequency content. Following this, texture segmentation may be considered as decomposition of a textured image in the form of a joint space-spatial frequency representation, by designing a bank of band-pass filters and the this information can be utilized to locate regions comprising similar content of local spatial frequency. Furthermore, based on the known fact that Gabor filter is able to produce different outputs corresponding to distinct textured regions present in an image, many studies have been done to design texture based segmentation models using Gabor filters. The work done by [11] has shown the better segmentation results using 1-D Gabor instead of using 2-D Gabor filter. Inspiring from this result, in this work, an attempt was done to design an optimal 1-D Gabor filters incorporating evolutionary genetic algorithm to get improved segmentation results for the complex natured retinal images. The application of matched filters is also discussed in [12].

2. METHODOLOGY USED

2.1 An Overview of Gabor Filters

The study done by [13] on mathematical modeling of visual cortical cells proposed a formalism of a structure of tuned band pass filter bank. It has been found that, in the frequency domain, these filters comprise Gaussian transfer functions. Furthermore, filter characteristics can be obtained by taking the inverse Fourier transform of this transfer function which closely resembles to the Gabor filters. However, the Gabor filter is viewed as a composition of Gaussian function modulated by a complex sinusoidal function. The Gabor filter can be described by the following equation:

$$f_g(x,y) = \frac{1}{2\pi\sigma_x\,\sigma_y} e^{-\frac{1}{2}\left[\left(\frac{x-x_0}{\sigma_x}\right)^2+\left(\frac{y-y_0}{\sigma_y}\right)^2\right]+2\pi j\,(U_x+V_y)} \tag{1}$$

where, σ_x and σ_y are variances along x and y axes respectively and U_x and V_y are center frequencies along x and y-axes respectively and x_0 and y_0 are center coordinates . However, 2D Gabor filter comprises Gaussian term, which has smoothing effect; it has been found that if 2D Gabor filter is applied to the image, the edges present in all direction in the image are smoothened out. This smoothing operation leads to the loss of important edge information, resulting lower segmentation efficiency. Therefore, instead of applying 2D Gabor filter, being a separable one, 1D Gabor filter can be applied in order to retain the important edge information. In this approach, edges are smoothened out along only those directions, where 1D Gabor filter is applied, leaving the edges intact in all other directions. If 1D Gabor filters are applied in both horizontal and vertical directions separately, their outputs can be combined to get better texture signature map. Moreover, the computational complexity gets lower in the application of 1D Gabor filter ($O(MN^2)$) in comparison to 2D Gabor filter ($O(M^2N^2)$), where MXN is the size of an image. After applying 1D Gabor filter on image I(p,q), yields output texture signature map I'(p,q) , described by following equations:

$$f_g(x) = \frac{1}{2\pi\sigma_x} e^{-\frac{1}{2}\left(\frac{x}{\sigma_x}\right)^2 + 2\pi j\,U_x} \tag{2}$$

$$f_g(y) = \frac{1}{2\pi\sigma_y} e^{-\frac{1}{2}\left(\frac{y}{\sigma_y}\right)^2 + 2\pi j\,V_y} \tag{3}$$

$$I_h(x,y) = I(x,y) \otimes f_g(y) \tag{4}$$

$$I_v(x,y) = I(x,y) \otimes f_g(x) \tag{5}$$

$$I'(x,y) = \sqrt{\left(I_h(x,y)\right)^2 + \left(I_v(x,y)\right)^2} \tag{6}$$

Eqn. (2) and (3) represents 1D Gabor filter along x and y-axes respectively. Eqn. (4) and (5) represents convolution of 1D Gabor filter with image along with x and y-axes respectively. However, the noise present in output texture signature map was decided to smoothen out by again passing it through Gaussian post filter. 2D Gaussian Filters being as separable one, again 1D Gaussian Filters were applied on this output texture signature map to smoothen noise and thus retaining the important edge information and also reduces the required number of filter operations. The output obtained from applying Gaussian Post Filter has reduced noise and its distribution is smoother more close to Gaussian as shown in Fig. 1. This nearly equivalent Gaussian distribution leads to make the task of texture-based classification easier in feature space, where it is formulated by combining the parameters of Gaussian distribution both mean and standard deviation.

2.2 Local optimization: Gradient Descent approach

In this work, gradient descent method was used for first order optimization and genetic algorithm was used to globally optimize the Gabor filter parameters. In gradient descent approach searching performs proportional to the negative of the gradient of the function at the current point to find the local minimum result and positive gradient for local maximum. If the function representation in feature space of the image is F(x) and it is defined and differentiable nearby point p, then its value gets decreases fastest along the direction of negative gradient, similarly its value gets increases fastest along the direction of positive gradient. The negative gradient of F(x) at point p is defined as $-\Delta$ F(p).

For next point q, if it follows as q = p - γ Δ F(p) for a given very small value of γ, then F(q) $\leq$ F(p). In this approach, one guess x_0 is considered as a point for initial local minimum of F (x) to start and then for sequence of points $x_0, x_1, x_2, x_3 \ldots$, and follows the condition such that;

$$x_{i+1} = x_i - \gamma_i \Delta F(x_i) \ , i \geq 0.$$

The local minimum convergence for the above sequence can be hopefully obtained if the following relation is satisfied:

$$F(x_0) \geq F(x_1) \geq F(x_2) \geq F(x_3) \ldots\ldots\ldots\ldots\ldots\ldots$$

The Gabor filter parameters were first order optimized using above-mentioned gradient descent method, resulting improved segmentation result.

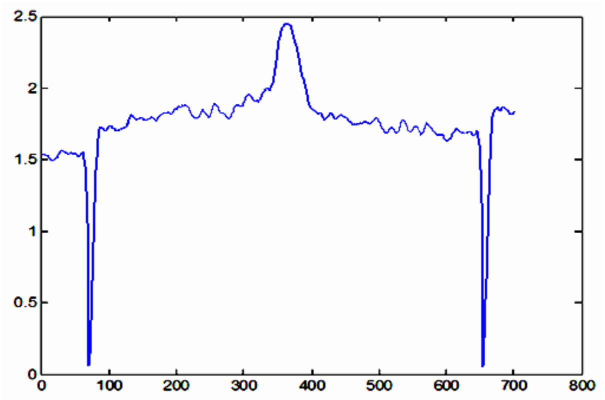


Figure 1: 'Almost Gaussian distribution' of output texture signature of Gabor filter applied on a retinal image

2.3 Global optimization: Genetic Algorithm (GA)

Genetic algorithm (GA) is an evolutionary algorithm which follows biological processes of natural selection and reproduction to find the solution for fittest. This can be used to find the global optimum solution for a given problem which computes the successive maximum and minimum value of a function. However, many of the processes of genetic algorithm involved in biological evolution are random, still the level of randomization and level of control can be fixed in this optimization technique [14]. The power and efficiency of these evolutionary algorithms are much better than other searching algorithms like random search and exhaustive search [15], as no extra information is required by them in advance about the given problem. Owing to this feature, Genetic algorithm has the ability to find the solution to those kinds of problems, which cannot be handled by other optimization techniques because of lack of differentiability, continuity, linearity or other characteristics.

Algorithm starts with generating initial population by randomly selecting parameters in search space. The genetic operators i.e. mutation, crossover, are applied to generate new population. The new individual is created based on bits and pieces of the fittest old individuals in every next generation. Though the genetic algorithms follow some random choices, but actually they are not simple random walk. However, the historical information is exploited by these algorithms in efficient manner to guess new search points expecting lead to get better performance. Each individual is evaluated applying fitness function and the newly created individual with improved fitness value is selected for success. These algorithms do not work on parameters as such, but first encode these parameters and then apply genetic operators. This encoding transforms the natural parameters of the optimization problem into a finite length string composed of some alphabets only. Searching is performed among a set of population points, not from a single point, resulting achievement of optimized value. The information about fitness value of the individual using fitness or objective function is being used by this algorithm rather using some other information i.e. derivatives or other auxiliary knowledge. This feature is exploited by GA, to solve those optimization problems having objective (fitness) functions which are non-continuous and non-differentiable.

2.4 Design of the Gabor Filters

This work is based on application of a combination of Gabor and Gaussian filters on retinal images. The output images obtained from these filters are analyzed by taking window frames of certain dimension (odd length) as samples. The statistical features, mean and standard deviation were extracted from each sample window and that window block was classified as a certain class of textured region by Nearest Neighbor classifier (NN) which follows minimum distance criteria. For this classifier, it is supposed that the textures present in the database can only appear in the images and the feature points corresponding to a particular texture are already known in advance for classification. This classifier needs to calculate the distance metric of a feature point corresponding to sample window block from all N feature points present in the feature database (N is total number of textures) and then it assigns a class (texture) number to the window block by texture number from which is closest. For better classification, this algorithm needs minimizing the overlap of different clusters formed based on distance metric corresponding to different classes of textures present in the database. In this work, this was achieved by tuning the filters. To obtain maximum discrimination between heterogeneous textured regions, filters were tunes in such a way that centroids of all the clusters should move away from each other, as shown in Fig. 2 (b). The correct classification of any feature point to a cluster is only possible if all the clusters are maximally separated (Non-overlapping) from each other. If the clusters are overlapping, it is not an easy task to assign a feature point to a cluster accurately, may get stuck in high probability of misclassification as shown in Fig. 2(a). The case shown in Fig. 2 (b) is for non-overlapping arrangement of clusters. The second case is not always possible for all the cases, still it is better to minimize the extent of overlap for most of the problems.

In Fig. 2, (x_i , y_i) is the centroids of the i-th cluster (texture class) and (x_j , y_j) is the centroids of the j-th clutser of feature points in feature space (in this case x_i is mean and y_i is standard deviation feature), the Euclidean distance $d_{ij\ (i\neq j)}$ is calculated by the formula (Eqn. 7):

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (7)$$

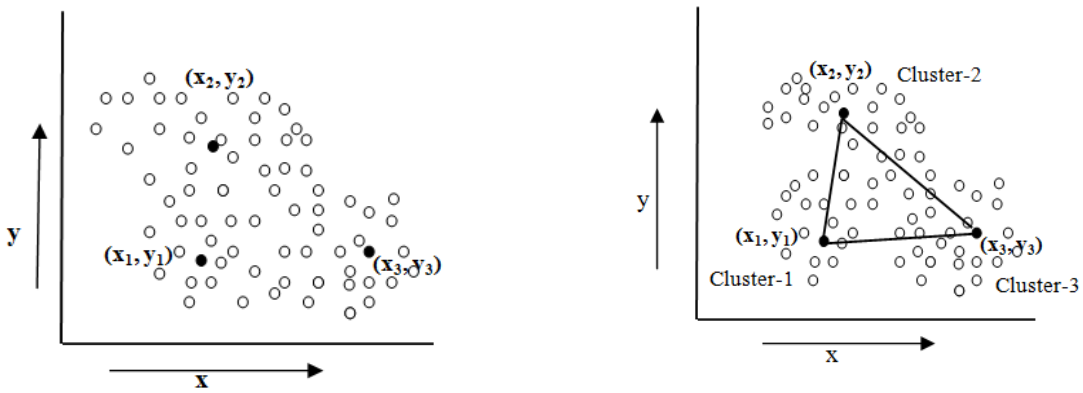
For non-overlapping clusters, in order to move away each other, the value of d_{ij} should be maximized. This goal can be achieved by maximizing only the minimum value among all d_{ij}, automatically lead to maximize others. Therefore, the criteria for objective function to be used in this works are as follows (Eqn. 8):

$$F_{obj} = \mathrm{MIN}\ (d_{ij}), \quad \forall\ i,j \text{ and } i \neq j \tag{8}$$

The main goal of filter design is choose the Gabor filter parameters such that objective function F_{obj} is maximized in order to move all clusters away from each other. However, this objective function is non-differentiable and discontinuous, deterministic optimization methods i.e. gradient descent method, Newton-Raphson, etc. cannot be able to solve these problems efficiently. Evolutionary based stochastic methods are found highly efficient for those kinds of optimization problems where the objective functions are non differentiable. The scale of Gabor filter is designed as per the size of Texel of the texture class. The criteria to derive the standard deviation (SD) were selected from the scale (S) of Gabor filter as shown in Eqn. (9).

$$2 * SD + 1 = S \tag{9}$$

The scale of post filter operation was also considered as scale of Gabor filter.



(a) Overlapping Clusters (high probability of misclassification)

(b) Non-overlapping Clusters (better classification)

Figure 2: Non-overlapping clusters based criteria for maximum discrimination

2.5 Procedure to optimize Gabor parameters (U, V) using Genetic Algorithm

The Gabor parameters (U, V) were tried to be optimized using Genetic algorithm, in order to maximize the objective function (F_{obj}). In this approach, these parameters were represented into bit string using GA tool, then after the evolutionary rules and operators were applied. Thereafter, the best individual (with best score) are chosen for next generations and consequently the objective function evaluates maximize in each generation. Sufficient number of generations was provided as stopping criteria to algorithm to run. Expecting that one may be able to get better result of the problem as the number of generations specified to the algorithm increases.

2.6 Overall structure of texture based filter and classification model

The model used in this work for texture based filtering and classification is discussed in Fig. 3. The segmented image is obtained by inputting a sample image to the filtering and classification model through various phases. Firstly input image is passed through Gabor Filters ($F_{g1}(x, y)$ to $F_{gn}(x, y)$); thereafter their outputs are tuned by magnitude operators (MOP_1 to MOP_n) and finally passed through Gaussian Post Filters ($F_{p1}(x, y)$ to $F_{pn}(x, y)$). These outputs are inputted into various intermediate classifier stages (CS_1 to CS_n) as shown in Fig. 3. These classifier stages use the Nearest Neighbor algorithm, which inherently work on minimum distance to find the closest class matching. Based on minimum distance, this classifier assigns a number to a pixel corresponding to a particular textured region to which it has highest matching (minimum distance). Finally these outputs of intermediate classifiers are fed into final classifier block to get segmented output image. The algorithm used in final classifier takes pixel wise information from all the images and classifies each pixel to that texture class to which the filter-bank classifier stage combination model has classified maximum number of times.

However, the pixel which is classified maximum number of times does not represent unique classification, is marked as unclassified and assigned a value zero. Thereafter, all the unclassified pixels are selected to find their NXN neighborhood (N is taken as an odd number to capture equal distributive texture feature through all directions) and is assigned to that textured region (class) to which maximum number of classified pixels of that neighborhood belong. This neighborhood based classification technique minimizes probability of misclassification. Edge detection technique was used to find edges by convolving vector [-1 0 1] and its transpose with the above mentioned classified image, resulting a completely segmented and classified image as an output. The accuracy of filter and classification model used was evaluated by defining a metric, "CA" to represent classification accuracy. It is calculated in the form of ratio of correctly classified pixels to the total number of pixels (expressed in percentage). The sample set of test images were used to evaluate this metric, whose classification results are known in advance as named ground truth.

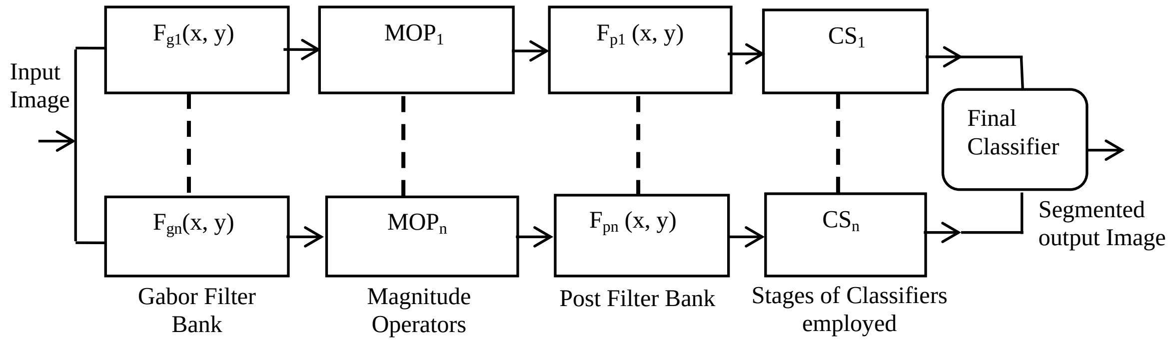


Figure 3: Block diagram of structure of filter and classification model

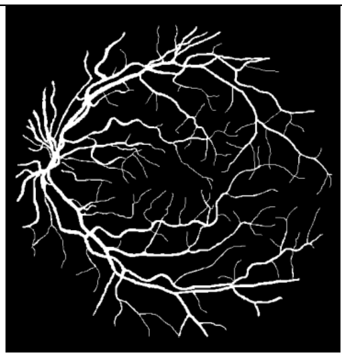
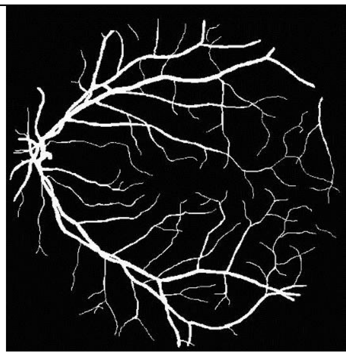
3. EXPERIMENTAL RESULTS

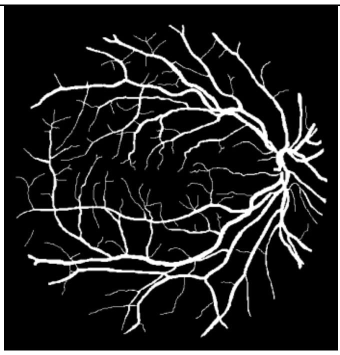
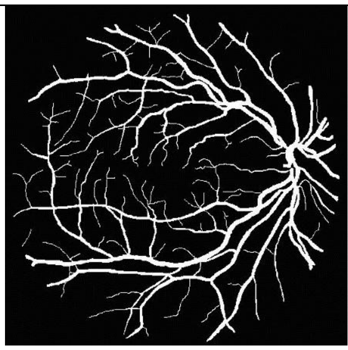
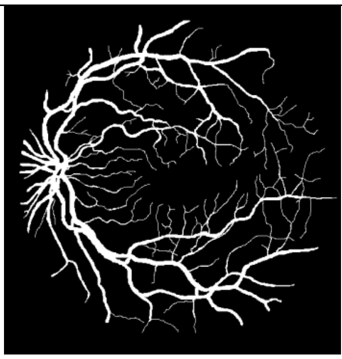
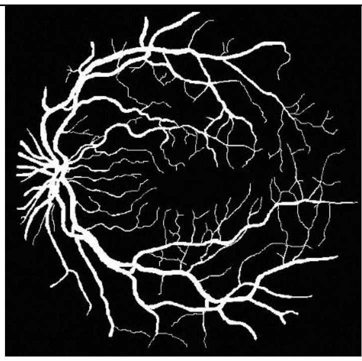
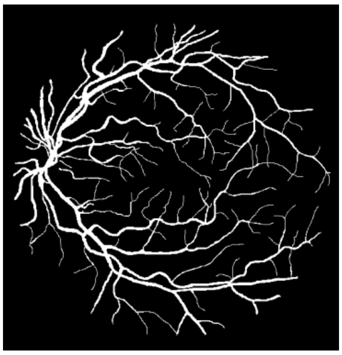
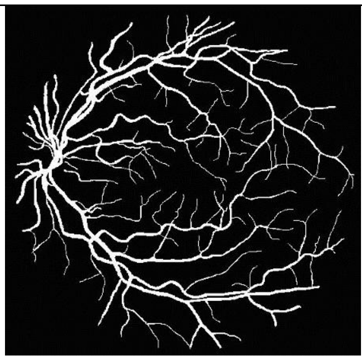
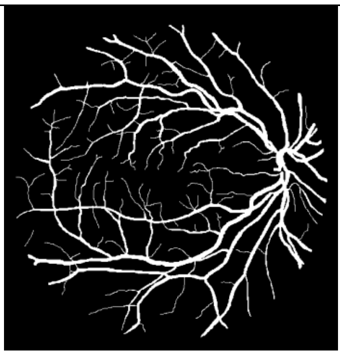
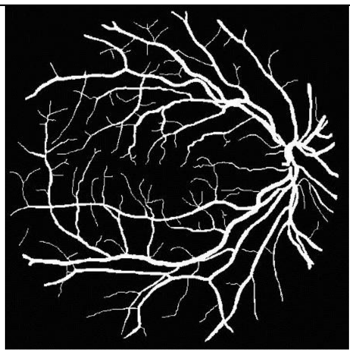
Data Collection: To illustrate the behavior of the methodology proposed in this work, medical image database DRIVE was downloaded from website [16], comprising 20 test and 20 training retinal fundus images. Test and training both set also comprises the manual segmented retinal images. These manual segmented retinal fundus images were considered to find the ground truth data (required to be known apriori) required to calculate the classification (segmentation) accuracy of filterbank-classification model. Matlab R2013a was used as a software tool for writing code and performing experiments of this paper's work.

The task of segmentation and classification, if retinal fundus images are considered as bi-partite images, such that it contains only two different textured regions, only one Gabor filter-Post filter cascade is required. In this approach, our objective is to form only two clusters and make them as far apart as possible. Thus, to accomplish it the Euclidian distance between their cluster center points needs to be maximized. However, in this case, the Gabor filter employed needs only local optimization technique i.e. Gradient descent method to tune its filter parameters, as the objective function used here is differentiable and continuous. The classification and segmentation results are shown along with segmentation accuracy and filter parameters as shown in Table 1.

The qualitative and quantitative results shown in Table 1 were obtained by optimizing the Gabor filter parameters using gradient descent method considering the presence of only two different textured regions in the image. However, considering the complexity of the retinal images, it appears that it may have more than two different textured regions. For this case, the objective function is neither continuous nor differentiable. Therefore, it needs global optimization technique, i.e. Genetic Algorithm. The following Table 2 shows some selective qualitative and quantitative segmentation and classification results by optimizing filter parameters using Genetic Algorithm.

Table 1. Qualitative and Quantitative results with Classification Accuracy using Gabor filter by optimizing filter parameters with Gradient descent method

Result set-1: Gabor Parameters: $\sigma_x = 7$, $\sigma_y = 7$, U = - 0.030008, V = 0.030008			
Original Image	Ground Truth Classification (standard Manual segmentation)	Classified Image using our protocol	Classificatio n Accuracy (CA) (%)
			82.309977

			81.149685
			81.003152
Result set-2: Gabor Parameters: $\sigma_x = 7$, $\sigma_y = 7$, U=0.001888 and V=-0.001888			
			82.985362
			82.116469

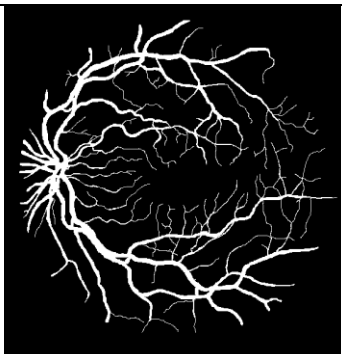
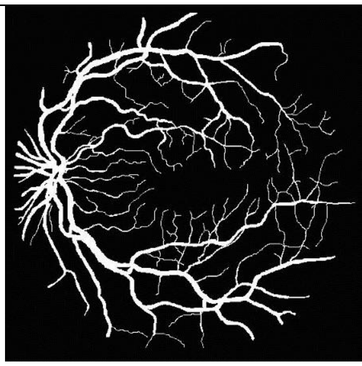
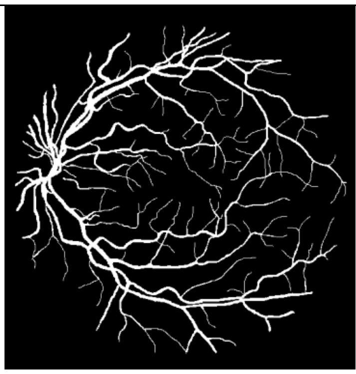
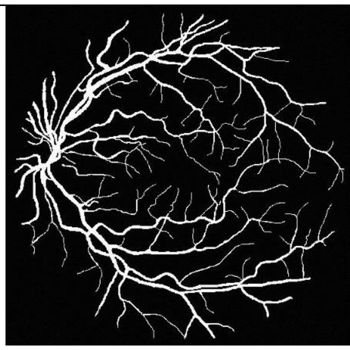
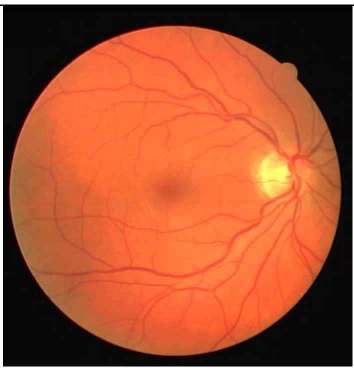
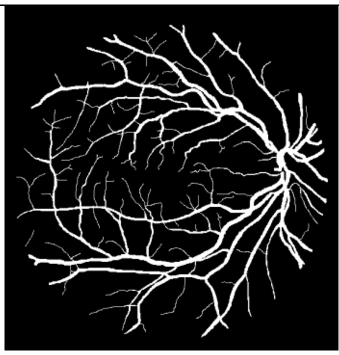
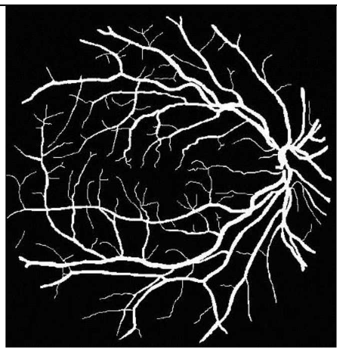
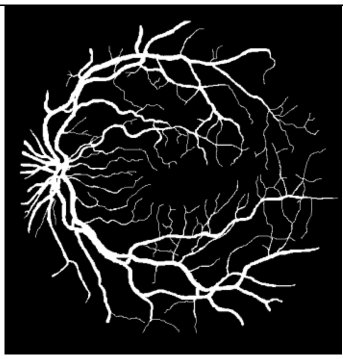
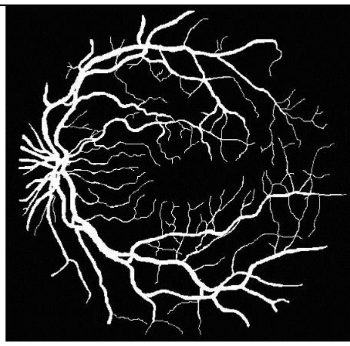
			82.079494
Result set-3: Gabor Parameters: $\sigma_x = 10$, $\sigma_y = 10$, U=-0.018934 , V=0.018934			
			83.519214
			82.536823
			82.930810
Overall Classification Accuracy (Accuracy ± standard deviation) = 82.2923 ± 0.8289			

Table 2. Qualitative and Quantitative results with Classification Accuracy using Gabor filter by optimizing filter parameters with Genetic Algorithm

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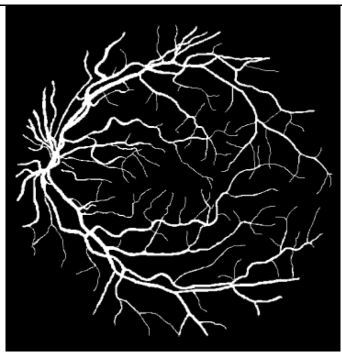
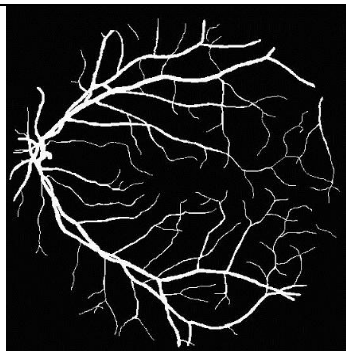
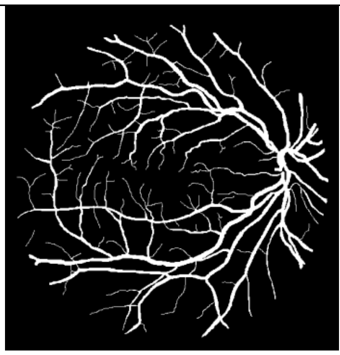
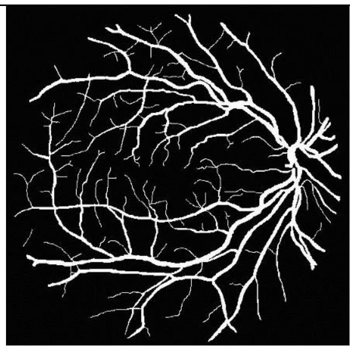
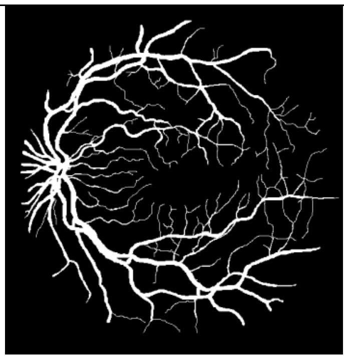
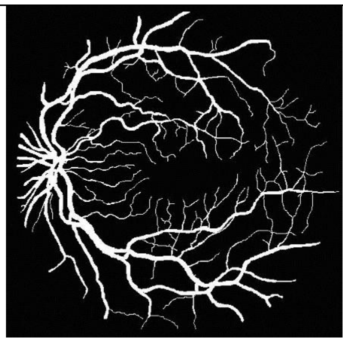
<tr><td>Original Image</td><td>Ground Truth Classification (standard Manual segmentation)</td><td>Classified Image using our protocol</td><td>Classification Accuracy (CA) (%)</td></tr>
<tr><td></td><td></td><td></td><td>83.808977</td></tr>
<tr><td></td><td></td><td></td><td>82.459685</td></tr>
<tr><td></td><td></td><td></td><td>82.024152</td></tr>
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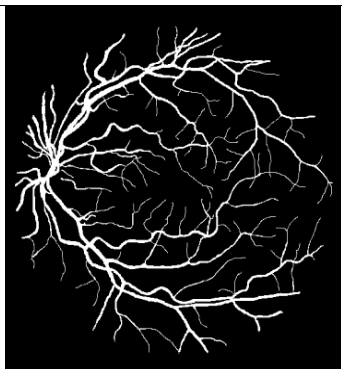
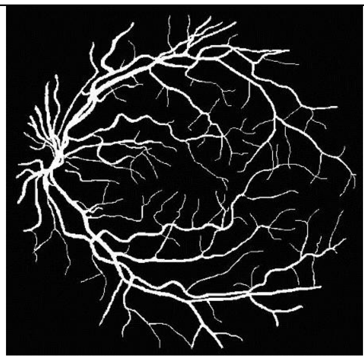
<tr><td></td><td></td><td></td><td>83.175362</td></tr>
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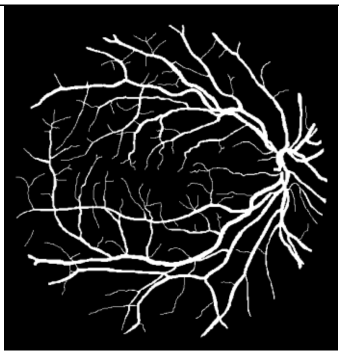
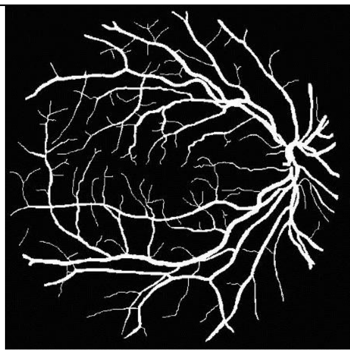
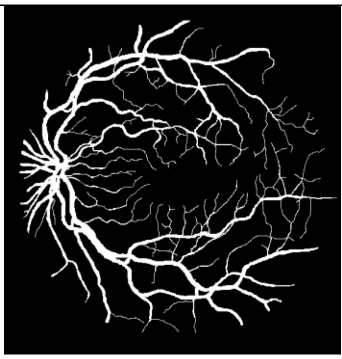
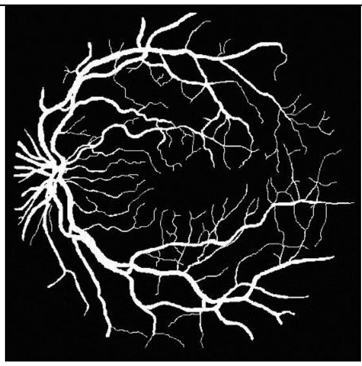
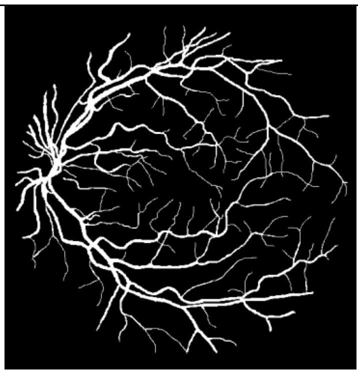
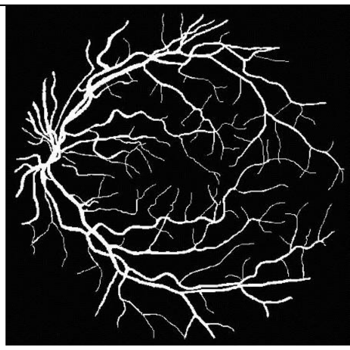
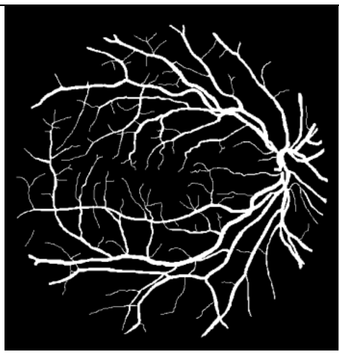
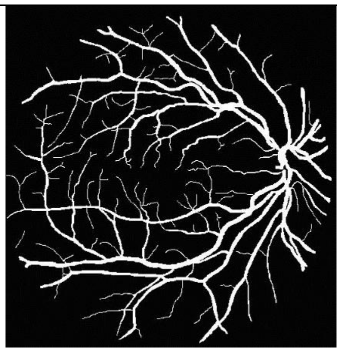
			83.118469
			83.389494
Result set-3: Gabor Parameters: $\sigma_x = 10$, $\sigma_y = 10$, U=-0.018934 , V=0.018934			
			83.979214
			83.337823

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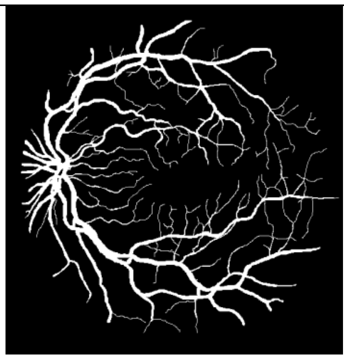
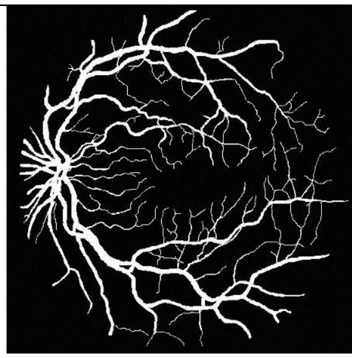
<tr><td></td><td></td><td></td><td>83.430810</td></tr>
<tr><td colspan="4">Overall Classification Accuracy (Accuracy ± standard deviation) = 83.1916 ± 0.6148</td></tr>
</table>

4. CONCLUSION

The segmentation of blood vessels is highly required process in diagnosis of diabetic retinopathy. This paper proposed a new method to automate the process of segmenting out the blood vessels from retinal images. The results obtained in this work provides mathematical and experimental evidence to promote applying Gabor filters on textured images, like retinal images, producing a crucial output characteristic signature, which helps in segmenting and classifying the images with better accuracy. As it is evident, the filters employed in an ideal autonomous texture segmentation tool, cannot be customized for single type of textures. Therefore, to capture the spreading and different orientation and frequency domain of the textures of interest, a bank of filters is required to implement the filter and classification model (Dunn et. al, 1995). This work showed the segmentation and classification of retinal images by applying Gabor and post Gaussian filter bank optimizing filter parameters firstly by Gradient descent method and finally by Genetic algorithm. The comparative results are shown in Table 1 and 2 with improved classification accuracy. As Genetic Algorithm (GA) is an evolutionary algorithm provides efficient global search in parameter space, employing GA only a few Gabor filter can be designed efficiently to obtain efficient classification and segmentation of multi-textured images. It is not always required the number of textures present in the image to be equal to number filters in filter-bank. It has been observed that for some cases, a smaller filter-bank (lesser number of filters than number of textures) produces more efficient discrimination for a given set of textures. However, the algorithm used in final classifier block (as shown in Figure 3) uses pixel-wise information for processing, consequently slow in speed in its inherent nature.

The classification work in this paper can also be extended to simulate the whole process of classification by an Artificial Neural Network (ANN). The standard manual segmented retinal images (prepared by trained medical expert) available in standard database (DRIVE) can be used to train ANN. Once ANN is trained properly, it will ready to take input data from the feature space and will assign a class (textured region) accordingly. The problem associated with the classification of overlapping clusters formed in some higher dimension can also be resolved using ANN as classifier. In such applications, the properly trained ANNs are found very efficient and fast in classification. The hybrid of trained ANN and tuned Filter-bank may be utilized in implementing a stand-alone automated system for real time multi-textured image processing applications.

5. ACKNOWLEDGEMENT

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