Genetic Algorithm Gabor Filter Optimisation for Automated Detection of Blood Vessels from Digital Retinal Images

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ABSTRACT
Automated vessel detection has great applicability in medical diagnosis for the purpose of detecting many diseases. Gabor filter is one of the most important methods in automated detection of blood vessels in digital retinal images. This paper proposes a new method to optimise the parameters of Gabor filter using Genetic Algorithm in order to improve its response. Several experiments were conducted to achieve better performance for Gabor filter: The area under the receiver operating curve and maximum average accuracy are used as fitness functions for the Genetic Algorithm. Also, an image is divided into 4 regions and a separate set of parameters was calculated for each region to find the best optimised parameters for each region. The results of the above 3 experiments are compared with previous vessel and edge detection techniques to prove the effectiveness of the proposed methods.

Keywords: Retina Image, Retinopathy, Vessel Detection, Gabor Filter, Genetic Algorithm, DRIVE.

1. INTRODUCTION
Retinal blood vessels are key to diagnose many human diseases (Gang et al., 2002). Diseases like diabetes and hypertension affect blood vessels' features and lead to restricted blood supply which may damage the retina and if deteriorated may cause blindness (Grisan et al., 2008).

The structure of retinal vessels provides information that is useful in detecting pathological changes in automated diagnostic systems. Traditional edge detection techniques, e.g. Sobel operator, and Prewitt operator do not perform efficiently in vessel detection problems as they perform the best when the edges are sharp and distinct (Gonzalez and Woods, 2002). However, retinal vessels are usually thin with low local contrast and they almost never have ideal step edges, therefore, the need for a specialised edge detection technique has emerged. Gabor filter is one of the most widely used techniques for the detection of blood vessels from retinal images (Rangayyan et al., 2008). Other techniques have also been proposed including matched filter (Chaudhuri et al., 1989), morphology edge detection (Zana and Klein, 2001), ridge-based vessel segmentation (Staal et al., 2005), Hough transformation (Zana and Klein, 1999) and wavelet transformation (Jorge, et al., 2001).

As Gabor filter is one of the main and best techniques used in vessel detection which has optimal localisation in both spatial and frequency domains (Rangayyan et al., 2008), it was chosen in this paper for further improvement on its performance. The aim of this paper is to optimise Gabor's filter parameters which are \( \tau \) (read tau) and \( \ell \) and to improve filter's response for blood vessels' detection utilising Genetic Algorithm (GA). This optimisation of Gabor's filter parameters is a major contribution of the work proposed in this research.

The rest of this paper is organised as follows: Section 2 reviews previous methods and techniques used in the area of vessel detection; the section also reviews the main concepts of the optimisation technique known as Genetic Algorithm (GA). Section 3 discusses the main steps used in the proposed methods to optimise Gabor's filter performance for the purpose of vessel detection using GAs. Section 4 discusses the results of the proposed techniques and makes comparisons with previous methods. Section 5 summarises the main

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findings of this paper and presents possible directions for future work.

2. LITERATURE REVIEW

Many researches have been going on in the area of vessel detection due to its medical importance. The usual approach is to detect blood vessels manually by ophthalmologists. However, automating the detection of retinal blood vessels offers many advantages over manual detection (Patton et al., 2006). It gives the chance to examine large number of images within short period of time and it reduces the cost and the workload required from manually-trained graders. Additionally, it gives more accurate resolution than manual detection which may allow for better characterisation and detection of the features of blood vessels.

2.1. Traditional Edge Detection

Traditional edge detection techniques including gradient methods like Sobel and Prewitt methods. In gradient edge detection methods, the edge is detected using neighbourhood differential operator; it detects edges by looking for the maximum and minimum in the first derivative of the 2-D image. The gradient of an image $f(x,y)$ at location $(x,y)$ contains two components $G_x$ and $G_y$:

\[
G_x = \frac{\partial f}{\partial x} \quad (1)
\]
\[
G_y = \frac{\partial f}{\partial y} \quad (2)
\]

The magnitude of gradient $\nabla f$ determines the maximum rate of change of $f(x,y)$ per unit distance as given in equation.

\[
\nabla f = \sqrt{G_x^2 + G_y^2} \quad (3)
\]

The direction of gradient is perpendicular to the edge direction and is given in the following equation:

\[
\alpha(x, y) = \tan^{-1}\left(\frac{G_x}{G_y}\right) \quad (4)
\]

Where $\alpha$ is measured with respect to the x-axis. Considering a 3X3 region of an image centred at Z5 as shown in Figure 1, Sobel and Prewitt operators are described next.

![Figure 1: A 3X3 region of an image](image)

Sobel is a 3X3 mask operator that implements the gradient method as described by Gonzalez & Woods (2002) in which a 3X3 mask is used and the gradients at point z5 which is illustrated in Figure 1 are:

\[
G_x = (Z_7 + 2Z_8 + Z_9) - (Z_1 + 2Z_2 + Z_3) \quad (5)
\]

And

\[
G_y = (Z_3 + 2Z_6 + Z_9) - (Z_1 + 2Z_4 + Z_7) \quad (6)
\]

A 3x3 Prewitt mask operator described by Ziou and Tabbone (1997) is proposed and the gradients are defined as follows:

\[
G_x = (Z_7 + Z_8 + Z_9) - (Z_1 + Z_2 + Z_3) \quad (7)
\]

And

\[
G_y = (Z_3 + Z_6 + Z_9) - (Z_1 + Z_4 + Z_7) \quad (8)
\]

Sobel operator emphasises the centre point by multiplying it by 2 in comparison with Prewitt operator.

Traditional edge detection techniques including gradient methods like Sobel and Prewitt methods are inefficient in detecting blood vessels because they are sensitive to noise, and they give inaccurate results with non-ideal edges, because the size of the kernel filter and coefficients are fixed. Additionally, these methods are not adaptable to distinguish a valid edge from an edge caused by noise (Gonzalez and Woods, 2002).

2.2. Vessel Detection

Specialised vessel detection techniques were proposed to focus on the problem of vessel detection rather than the general problem of edge-detection. Such specialised techniques include: Model-based techniques, Classifier-Based Techniques and Vessel Tracking techniques as explained next.

2.2.1. Model-Based Techniques

In this category a 2-Dimensional (2D) Gaussian
shaped filter is used to detect vessels. Figure 2 shows the intensity of the cross section profile of retinal vessels, notice that it has an up-side-down Gaussian shape. Two types of filters belong to this category: matched filter and Gabor filter.

Matched filter is a Gaussian shaped filter that was originally proposed by Chaudhuri et al. (1989), and then improved by Hoover et al. (2000) and later by Al-Rawi et al. (2007a; 2007b). Matched filter detects vessels by filtering and thresholding the original image. It has the advantage of simplicity and effectiveness. It utilises of the prior knowledge that the cross-section of the vessels can be approximated by a Gaussian function. Therefore, a Gaussian-shaped filter can be used to “match” the vessels for detection (Chaudhuri et al., 1989; Zhang et al., 2010).

Matched filter is based on the following assumptions:
1. Vessels have small curvature so they can be approximated by piece-wise linear segments.
2. Vessels are darker than background and their intensity profile can be approximated by a Gaussian curve.
3. Vessels have constant width.

Matched filter is defined as:

\[
f(x, y) = \frac{1}{\sqrt{2\pi s}} \exp\left(-\frac{x^2}{2s^2}\right) - m,
\]

for \(|x| \leq ts, |y| \leq L / 2\) \hspace{1cm} (9)

Where s represents the scale of the filter and m is given as

\[
m = \frac{\int_{-\pi}^{\pi} \frac{1}{\sqrt{2\pi s}} \exp\left(-\frac{x^2}{2s^2}\right) dx}{2ts}
\]

m is used to normalise the mean value of the filter to 0 so that the smooth background can be removed after filtering, and L is the length of the neighbourhood along the y-axis to smooth noise. The criterion t is a constant and is typically set to 3 because more than 99% of the area under the Gaussian curve lies within the range [3s, 3s]. The parameter L is also selected based on s. When s is small, L is set relatively small, and vice versa. In the implementation, matched filter detects vessels by rotating it to all directions, and recording the maximum response for each pixel (Chaudhuri et al., 1989; Zhang et al., 2010).

The matched filter method was then improved by Hoover et al. (2000) by probing different regions in the matched filter response image according to global image’s attributes. During each probe, the threshold is determined according to certain criteria, then the area is classified to be either a blood vessel or not, in this way different probed areas are thresholded with different thresholds through the image.

Al-Rawi and Karajeh (2007) also proposed another method for improving matched filter by using GA to search for the matched filter’s parameters that give the best result, the filtered image is thresholded with different threshold values between 0 and 1, and each threshold produces a different binary image.

Gabor filter was originally introduced by Dennis Gabor (1946) for filtering of one dimensional signal. It is obtained by modulating a sinusoid with a Gaussian.

Daugman (1985) extended the Gabor filter to 2D signals. These filters were successfully used to extract biased attributes from human iris. Daugman observed that in 2D form, resolution for the two coordinates (sinusoid orientation and the Gaussian) of spatial position enters into an uncertainty relation with resolution for the two coordinates of the 2D spatial frequency domain, and that the optimal solution to this joint 2D uncertainty problem supported a family of functions consisting of bivariate elliptic Gaussians modulated by sinusoidal plane waves (Jones and Palmer, 1987).

Rangayyan et al. (2008) proposed the use of Gabor filter for vessel detection by converting each pixel in the retinal image to a luminance component before filtering. The real Gabor filter kernel (or mother wavelet) oriented
at the angle $\theta = -\pi /2$ may be formulated as (Rangayyan et al., 2008):

$$G(x, y) = \frac{1}{2\pi \sigma_x \sigma_y} \exp \left( -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right) \cos(2\pi f_0 x)$$

(11)

This filter is described in more details in section 3.2 as it is the core of the work proposed in this paper.

2.2.2. Classifier-Based Techniques

These techniques include two steps: segmenting the image into connected regions, then each region is classified into either vessel or non-vessel according to many features.

Adaptive local thresholding is introduced by Jiang and Mojon (2003). In this approach a binary image is obtained after applying a threshold, then this image is used in a classification procedure to accept or reject any region in the image as a certain object. A series of different thresholds are applied and the final detection result is a combination of the results provided by individual thresholds.

Staal et al. (2005) introduced the ridge-based method that extracts the image ridges (points coincide with vessel centres), then ridges are grouped into sets, a feature vector is computed for every pixel depending on patches and ridges.

Soares et al. (2006) proposed an algorithm that uses Gabor filters for feature vector pixel classification. David et al. (2008) used Artificial Neural Networks (ANN) classifiers to detect retinal vessels.

2.2.3. Vessel Tracking Techniques

Vessel tracking approach works by first locating the centre of vessel cross-section, the vessel width and direction then exploit local image properties to trace the vessels recursively. This approach is based on region growing. The drawbacks of this approach are that it requires intervention from the user and its performance is affected by vessels bifurcations (Jung and Hong, 2006).

2.3. Genetic Algorithm

Genetic Algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimisation and search problems (Gang et al., 2002; Mitchell, 1975; Thede, 2004). In this paper GA is used to calculate the best values for Gabor's filter parameters that are used to achieve the best fitness value. The fitness is used as a measure of how successful a solution is in detecting vessels, the better the detection, the better the solution and the higher the fitness. GA starts with a set of initial solutions called initial population. Each population is used to generate another population to find better solutions. When a new population is generated new solutions (individuals) are born while other solutions die.

The generated solutions (individuals) are selected according to their fitness, the fitness of an individual is a measure of how suitable is the solution (individual) to solve the problem, the fitness of the solution is evaluated using a fitness function (objective function). Each individual is represented by a binary string which is called a chromosome; the length of the string depends on the problem's encoding or representation. The main attributes of GAs are: The fitness function, encoding, selection (elitism), crossover, and mutation.

2.3.1. The Fitness Function

The fitness function is the function of the problem that is being solved or searched, the fitness function is used to assign a fitness value for each chromosome (possible solution to the problem). The fitness value determines how much a chromosome is close to the optimal solution of the problem. An individual (chromosome) with a higher fitness represents a better solution to the problem. As such, the higher the fitness value for a chromosome, the higher the probability that chromosome would survive for coming generations.

2.3.2. Encoding

Encoding is the way in which chromosomes are represented to be input for the fitness function. There are many types of chromosomes' encoding includes: binary encoding, value encoding, and permutation encoding.

2.3.3. Selection (Elitism)

Selecting parent individuals according to their fitness to generate new individuals (children), selection includes Roulette wheel selection, rank selection, and elitism. Elitism copies the best chromosomes in the old population to the new population directly to guarantee that the highly fitting chromosomes are not missed from the new generation which ensures that the new generation is not worst than the old one.
2.3.4. Crossover

After the elitism process ends, crossover operation starts by changing some genes (bits) in parent chromosomes to create children (offspring). There are many types of crossover including: single-point crossover, two-point crossover, and uniform crossover. By mixing the characteristics of parents, new children may combine the best features of their parents.

2.3.5. Mutation

Mutation takes place after crossover to make the distribution of chromosomes investigate all possible solutions, by randomly mutating bits in individual parents to create new children with modified genes (characteristics).

3. OPTIMISING GABOR FILTER USING GENETIC ALGORITHM

This section presents a detailed description of the proposed methods in this paper.

3.1. Image Preparation

All the experiments were implemented using DRIVE database that is described by Staal et al. (2005); a set of 40 images that were divided into a training set and a test set, both containing 20 images, with their manual segmentations of the vasculature, that are segmented by ophthalmologists who marked all pixels that were at least 70% certain that they are vessels. All of the images contained in the database were actually used for making clinical diagnoses. The green band of each RGB retinal image is extracted for filtering. The green band is chosen since it determines image features and to compare our results with previous methods in the literature which used green band. After extracting the green band, the image's intensity is inverted, so vessels become of positive contrast than the background, therefore it can be filtered by Gabor filter. The image is then masked using the corresponding mask image in DRIVE database to identify the boundaries of the effective region, or the Field of View (FOV).

3.2. Image Filtering

The real Gabor filter kernel (or mother wavelet) oriented at the angle $\theta = -\pi/2$ that was used by Rangayyan et al. (2008) to detect blood vessels may be formulated as:

$$G(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right) \cos(2\pi f_0 x)$$

(12)

Where $\sigma_x$ and $\sigma_y$ are the standard deviation values in the x - and y- directions for the vessel intensity profile, and $f_0$ is the frequency of the modulating sinusoid. A bank of 180 filters is used by rotating the kernel in the range of $\theta = [-\pi/2, \pi/2]$, so the maximum response of these filters is recorded to be taken into account. The parameters of Gabor filter which are $\sigma_x$, $\sigma_y$, and $f_0$ are calculated from the vessel's structure as following:

The amplitude of the exponential (Gaussian) term in (12) is reduced to one-half of its maximum at $x = \tau/2$ and $y = 0$ where $\tau$ is the thickness of the line detector. Therefore:

$$\sigma_x = \tau/2\sqrt{2\ln2}$$

(13)

The cosine term has a period of $\tau$; hence,

$$f_0 = 1/\tau$$

(14)

The value of $\sigma_y$ could be defined as

$$\sigma_y = \ell\sigma_x$$

(15)

Where $\ell$ determines the elongation of the Gabor filter in the orientation direction with respect to its thickness. The value of $\tau$ is varied to prepare a bank of filters at different scales for multi-resolution filtering and analysis.

Rangayyan et al. (2008) used Gabor filter to detect retinal blood vessels, in this method each pixel is converted to a vector of colour components and then each component is normalised by dividing its value by 255, the result is converted to the luminance component $Y$, computed as follows:

$$Y = 0.299R + 0.587G + 0.114B$$

(16)

Gabor filter extends each image beyond the effective region to avoid edge artifact. For each set of Gabor parameters ($\tau$, $\ell$) the highest response of applying Gabor filter is obtained over 180 angles and then the filtered
image is thresholded using sliding threshold, and compared to a ground truth image to obtain the True Positive Fraction (TPF) and the False Positive Fraction (FPF) to aid in measuring the filter’s performance as described in section 3.3.

3.3. Filter's Performance
In order to measure the filter's performance, the filtered image should be compared to the corresponding hand-labelled image from the DRIVE database. Two methods of comparison are used in this work; these methods are explained as following.

3.3.1. The Area Under The Receiver Operating Curve (ROC)
The first step in calculating the ROC is by filtering the image using the parameters (τ, ℓ) to produce a gray-level image with intensities between 0 and 1. A sliding threshold between the values 0 and 1 in step of 0.001 is applied on the filtered image to obtain 1000 binary images.

For each binary image, the True Positive Fraction (TPF), and the False Positive Fraction (FPF) are calculated as following:

\[
TPF = \frac{\text{True vessel pixels}}{\text{vessel pixels in hand - labelled image}}
\]  \hspace{1cm} (17)

And

\[
FPF = \frac{\text{False vessel pixels}}{\text{non - vessel pixels in the hand - labelled image}}
\]  \hspace{1cm} (18)

The true vessel pixels are those pixels that are detected as vessel pixels in the resulted image and these pixels are actually vessel pixels in the hand-labelled image, and the false pixels are those pixels that are detected as vessel pixels in the resulted image, but they are non-vessels in the hand-labelled image. Hand-labelled images are obtained from the retinal image by a human expert to be used for comparisons purposes with automatically detected vessels (Staal et al., 2005). ROC curve is a graphical plot of FPF versus TPF, and the larger the area under the curve, the better the performance of the filter.

3.3.2. Maximum Accuracy (MA)
MA is calculated as following: After thresholding the filtered image as mentioned in the previous subsection, the accuracy is calculated for each binary image by calculating the sum of true vessel pixels and true non-vessel pixels and dividing the sum by the number of Field of View (FOV) pixels, which is the circular area in the retinal image. Then MAs for the 1000 thresholds are used to calculate the Maximum Accuracy. The Maximum Average Accuracy (MAA) is the average MA over all the 20 images of DRIVE database.

3.4. Settings of Genetic Algorithm
As mentioned earlier, there are two parameters of Gabor filter that must be optimised in order to improve the performance of Gabor filter; these parameters are τ and ℓ. GA is used to calculate the values of these parameters that give the best Gabor filter response, the main procedures for GAs setting is to determine the encoding criteria, the fitness function and the GAs parameters (Gang et al., 2002; Mitchell, 1975; Thede, 2004).

3.4.1. Encoding
Value encoding is used in this work, since the parameters τ and ℓ are real numbers; therefore each chromosome is represented by two variables τ and ℓ. Each chromosome represents a possible Gabor filter with values for τ and ℓ.

3.4.2. The Fitness Function
The fitness function of the GA depends on the problem that is to be optimised, the optimisation depends on the two comparison measurements for Gabor filter performance which were explained in the previous sections. These measurements are:

- The Area under ROC.
- MA.

3.4.3. GAs Parameters
To calculate the best value of the fitness function, some of GA's parameters that are problem-dependent need to be determined, these parameters are:

i. Population size: This parameter determines how many chromosomes are in a population. The larger the population size, the better the chance that an optimal solution will be found. The population size depends on how complicated the computation of the problem is, and so it affects the speed of GA. Due to the intensive computations in this work, a moderate population size of
30 is chosen.

ii. **Elite count**: Elite count determines how many solutions (individuals) from the current generation are chosen to survive to the new generation without being crossover or mutated, elite number should be low, to give chance to the new population to be different from the old one, so it is chosen to be 2.

iii. **Crossover rate**: It determines how often crossover is performed, if there is no crossover, then the offspring is an exact copy of parents, generally crossover rate should be high to produce new chromosomes, so it is chosen to be 80% of the population; i.e. 24. The used crossover function is heuristic multipoint.

iv. **Mutation rate**: It determines how often will be some parts of the chromosome be mutated. If there is no mutation, offspring is taken after crossover without any change. The mutation rate should be low.

Therefore, the 2 individuals, having the highest fitness value are copied directly from each generation to the next one (elitism), and the number of crossover individuals equals \(30 \times 0.8 = 24\), then 4 individuals are mutated.

Some notes about the implementation details of the GA are:
- Gabor filter is rotated by an angle of 2.
- The population of the chromosomes is randomly initialised to values between (0, 5) for \(\ell\) and (0, 15) for \(\tau\).
- GA is run up to a certain number of generations or until there is no further improvement in the fitness value.
- Reinitialising and running GA again using the same settings may not result in the same filter parameters due to the different random operations that GA follows.

### 3.5. The Proposed Methods

This section presents a detailed description of the methods that are used in this work and their block diagrams.

#### 3.5.1. Optimising the Average Area Under ROC for All DRIVE Database Images

In this method, the fitness function of GA is the average area under ROC for the 20 DRIVE images, as the ROC for the 20 images is used; it is called the average area under ROC. The block diagram of this method is shown in Figure 3. The green band image is extracted for each of the 20 images of the training set of the DRIVE database. Then each green band image is filtered using Gabor filter, the filtered image is then thresholded in step of 0.001 of threshold values between 0 and 1. For each thresholded image TPF and FPF are calculated and ROC curve is plotted, and the area under ROC is calculated for each image. The average area under ROC for the 20 images is the fitness function of GA.

#### 3.5.2. Optimising the average MA for the all DRIVE Database Images

In this method the fitness function of GA is the average MA for the 20 images of DRIVE database, the block diagram of this method is shown in Figure 4. The first stage in image preparation is the extraction of the green band image for each of the 20 images of the training set of the DRIVE database. Then each green band image is filtered using Gabor filter, the filtered image is then thresholded in step of 0.001 of threshold values between 0 and 1. For each thresholded image the accuracy is calculated and the MA is taken into account for each image then the average MA of the all 20 images MAA is the fitness function of GA.

#### 3.5.3. Dividing The First DRIVE Image Into 4 Regions

After extracting the green-band from the first image of DRIVE database, it is divided into 4 equal regions as show in Figure 5, then the area under ROC for each region is calculated using different Gabor filter parameters for each region, and the average of the area under ROC is calculated and so the fitness function of the GA is the average area under ROC of the areas under ROC of the 4 regions. The rationale behind this method is to find the best parameters for each region, when different set of parameters are used for each region, they are going to be optimised for that region and better accuracy is expected. The use of 4 regions is just an illustration of the use of specific parameters for each region; more or less regions could be used. The block diagram that describes this method is shown in Figure 6.

### 4. SIMULATION AND RESULTS

The results of the proposed methods in this paper are as following.
Figure 3: Optimising the Average Area under ROC for All DRIVE Database Images Block Diagram.
Figure 4: Optimising the Average MA for all DRIVE Database.

Figure 5: Dividing the Green Band of the First DRIVE Image into four equal regions.
4.1. Optimising the average area under ROC for all DRIVE database images

In this method, the 20 images of the DRIVE database were used as an input for the GA optimisation. After calculating the ROC for each Gabor-filtered image, the average area under ROC for the 20 images is the fitness function of the GA, since GA gives the minimum value and in this experiment the maximum result for average ROC is desired.

The parameters that gave the best result after applying GA are \( \tau = 10.352 \) and \( \ell = 1.541 \), and the corresponding average area under ROC = 0.9340.

Table 1 shows the area under ROC for DRIVE images using this method vs. previous edge-detection and vessel-detection methods.

4.2. Optimising the average MA for the all DRIVE database images

In this method, the 20 images of the DRIVE database were used as an input for the GA optimisation. After calculating the MA for each Gabor-filtered image, the average MA for the 20 images is the fitness function of the GAs, similar to the previous experiment as the maximum average MA is desired and GA gives the smallest result, a negative sign is added.

The parameters that gave the best result after applying GAs are \( \tau = 9.902 \) and \( \ell = 0.556 \), and the average MA = 0.94.

Table 3 shows the MA for DRIVE images using this method vs. previous edge-detection and vessel detection methods. This method optimises MA; nevertheless the behaviour of Gabor filter in terms of ROC is also studies. Table 4 shows the area under ROC for DRIVE images...
using this method vs. previous edge detection and vessel detection methods.

4.3. Dividing The First DRIVE Image Into 4 Regions

The fitness function for the GA is -(the average area under ROC) for the 4 regions. After applying GA, the parameters that gave the best results are: for region 1 \((\tau=9.33\) and \(\ell=1.564\)), for region 2 \((\tau=8.379\) and \(\ell=1.145\)), for region 3 \((\tau=9.714\) and \(\ell=1.221\)), and for region 4 \((\tau=9.814\) and \(\ell=1.179\)).

The average area under ROC = 0.95035. Figure 7 shows the ROC curve for the first image of DRIVE database for this method vs. Gabor filter (Rangayyan et al., 2008) and matched filter (Chaudhuri et al., 1989).

It can be realised that this work improves the average area under ROC obtained using Gabor filter (Rangayyan et al., 2008) and matched filter (Chaudhuri et al., 1989). It can be realised that this work improves the average area under ROC obtained using Gabor filter (Rangayyan et al., 2008) and matched filter (Chaudhuri et al., 1989).

4.4. Summary of Results

This section presents an overall summery of the implementation's results. Table 6 shows the average area under ROC for the methods proposed in this work compared with previous methods.

It can be noticed from the table that the best average area under ROC for Filter 1 is the best among all methods, it improves the result of Gabor filter (Rangayyan et al., 2008) by 0.01 and improves matched filter (Chaudhuri et al., 1989) by 0.13, these differences could be essential in diagnosing many diseases.

To check whether there is a significance difference between the results obtained using filter 1 and those results obtained using Rangayyan and Chaudhuri, a t statistical test is performed with the degree of freedom equals 19 as there are 20 images. The t-value between filter 1 and Chaudhuri’s matched filter equals 1.3252 which corresponds to a p-value of about 0.1. This indicates that the differences are significant at the 10% significance level; i.e. the differences are significant at any \(\alpha\geq 0.1\). This is translated to significant improvement due to the use of this filter over matched filter at the 90% confidence level. The t-value between filter 1 and Rangayyan’s et al. Gabor filter equals 0.2917 which indicates that the difference is not significant; nevertheless the difference is critical in diagnosis of many diseases.

Table 1: Results of Area under ROC for Filter1 Vs. Previous Methods.

<table>
<thead>
<tr>
<th>Image #</th>
<th>Filter1 (\tau=10.352, \ell=1.541)</th>
<th>Rangayyan</th>
<th>Chaudhuri</th>
<th>Sobel</th>
<th>Prewitt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image1</td>
<td>0.9473</td>
<td>0.9422</td>
<td>0.8357</td>
<td>0.7325</td>
<td>0.7322</td>
</tr>
<tr>
<td>Image2</td>
<td>0.9456</td>
<td>0.9415</td>
<td>0.822</td>
<td>0.7611</td>
<td>0.7591</td>
</tr>
<tr>
<td>Image3</td>
<td>0.9355</td>
<td>0.9330</td>
<td>0.8145</td>
<td>0.7088</td>
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</tr>
<tr>
<td>Image4</td>
<td>0.9224</td>
<td>0.9182</td>
<td>0.8025</td>
<td>0.767</td>
<td>0.7646</td>
</tr>
<tr>
<td>Image5</td>
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<td>0.9273</td>
<td>0.8299</td>
<td>0.7369</td>
<td>0.7362</td>
</tr>
<tr>
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### Table 2: Results of MA for Filter1 Vs. Previous Methods.

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<th>Chaudhuri</th>
<th>Sobel</th>
<th>Prewitt</th>
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### Table 3: Results of MA for Filter2 Vs. Previous Methods.

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<th>Chaudhuri</th>
<th>Sobel</th>
<th>Prewitt</th>
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Table 4: Results of Area under for ROC Filter2 Vs. Previous Methods.

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<td><strong>0.7264</strong></td>
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</table>

Figure 7: ROC for Each Region of the First DRIVE Image vs. Rangayyan’s et al. Gabor filter (Rangayyan et al., 2008) and Chaudhuri’s et al. matched filter (Chaudhuri et al., 1989).
Table 5: Results of Area under ROC Filter3 Vs. Previous Methods. Rangayyan’s et al. Gabor filter and Chauduri’s et al. matched filter

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<th>Chaudhuri</th>
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Table 6: Summary of the Average of Area under ROC.

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<th>Method</th>
<th>Filter1 $\tau=10.352$, $\ell=1.541$</th>
<th>Filter2 $\tau=9.902$, $\ell=0.556$</th>
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<th>Chaudhuri</th>
<th>Sobel</th>
<th>Prewitt</th>
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Table 7: Summary of the Average of MA.

<table>
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<th>Filter1 $\tau=10.352$, $\ell=1.541$</th>
<th>Filter2 $\tau=9.902$, $\ell=0.556$</th>
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<th>Chaudhuri</th>
<th>Sobel</th>
<th>Prewitt</th>
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<tbody>
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</table>

Table 7 shows the average MA for the methods that are presented in this work compared with previous methods. It can be noticed from the table that Filter 2 has the best results among all methods as it improves Gabor filter by 0.0014 and it improves matched filter by 0.06. A t statistical test is performed with the degree of freedom equals 19 as there are 20 images. The t-value between filter 2 and Chaudhuri’s matched filter equals 1.3031 which corresponds to a p-value of about 0.1. This indicates that the differences are significant at the 10% significance level; i.e. the differences are significant at any $\alpha \geq 0.1$. This is translated to significant improvement due to the use of this filter over matched filter at the 90% confidence level. The t-value between filter 2 and Rangayyan’s et al. Gabor filter equals 0.2107.

Figure 8 shows the ROC plot for filter 1 and filter 2 vs. previous methods, it can be realised that filter 1 that was obtained using average ROC as a fitness function has the largest area under ROC. Figure 9 illustrates the use of the new filters. In the figure the first DRIVE image was filtered using the new methods and previous methods. From the figure, it is clear visually that the new filters outperform the previous methods in blood vessels detection accuracy.

5. CONCLUSIONS AND FUTURE WORK

This section summarises the main conclusions of this research and outlines avenues for future research directions.

5.1. Conclusions

Retinal blood vessels are used by ophthalmologists to diagnose many diseases such as diabetes. Therefore, automating the extraction and detection of retinal blood vessels gives many advantages over manual detection, and facilitates the diagnosing process.

Many researchers worked in the field of vessel detection due to its medical importance, the main approaches that were examined in this paper are traditional edge detection techniques including Sobel and Prewitt operators, and modelled-based vessel detection techniques including matched and Gabor filters.

In this paper Gabor’s filter parameters were optimised using Genetic Algorithm (GA) to maximise the response of Gabor filter in detecting retinal blood vessels. Optimisation Gabor’s filter parameters using GA is a time-consuming but it is done once. After finding the best set of parameters, these parameters are used in Gabor filter for the detection of blood vessel in new retinal images.
For the sake of optimisation, three methods were introduced, each method aims to optimise Gabor filter depending on a different measuring factor. After comparing our results with previous methods, this work was found to improve all the previous methods in terms of average area under Receiver Operator Characteristics (ROC) and average Maximum Accuracy (MA) for the 20 DRIVE image, expectedly filter 2 did not improve average area under ROC because the optimisation emphasis was on MA only.
The Result of Rangayyan et al. Filter

The Binary Version of Rangayyan et al. Filter

The Result of Chaudhuri et al. Filter

The Binary Version of Chaudhuri et al. Filter

The Result of Sobel Filter

The Binary Version of Sobel Filter

The Result of Prewitt Filter

The Binary Version of Prewitt Filter

Figure 9: Retinal Image from DRIVE database with its hand-labelled vessels. The Image is filtered using the proposed techniques and the previous methods.

This paper differs from previous efforts in blood vessel detection according to:

— Using Genetic Algorithm (GA) to improve Gabor filter in blood vessels' detection.
— Using a multi-scale thresholding of gray-levels to find all the possible blood vessels.
— Using ROC as the fitness function for GAs.
— Using MA as the fitness function for GAs.
— Dividing the first DRIVE image into four regions, and calculating different Gabor parameters for each region.

5.2. Future Work

There are many domains still open for research in the field of using Gabor filter in vessel detection. The following are some possibilities for future research:

— Minimising the time taken by GA for optimising the filtering parameters as the main drawback of the work proposed in this paper is the time taken by GA to optimise Gabor’s filter parameters.
— Optimising Gabor filter in vessel detection using other optimisation methods like successive approximation.
— Optimising the time taken by Gabor for the filtering process.
— Using another images’ database as benchmark such as STARE (McCormick and Goldbaum, 1975).

REFERENCES


الاستخدام الحسابي الجيني لتطوير الأداء ذو الفلتر الغاني في تحديد الألياف الدمى في الصور الرقمية للشبكة العينية.

البحثية الأدوار تغريزة إلى تحسين وتيرة الأداء الأمثل لSTEMA في الفلتر الغاني أثناء تحديد الألياف الدمى، وتشمل الحالة التالية:

- تضمن تحصين لصورة قصيرة ودقة الناتجة (MA) للصورة الرابعة التحسيمية. وتم استخدام مساحة ROC للصورة القصيرة ودقة الناتجة (MA) الأربعة التحسيمية كخطبة ل ámbالاً السيطرة والمفاقمة بفضل الفلتر الغاني.

المصطلحات: شبكة العين، شبكة العين، الشبكة العينية، العلاج بالبيانات، جهاز Gabor، الفلتر الغاني، تحديد الألياف الدمى، الفلتر الغاني في الأداء الأمثل، الطرق الأهم، الفحص بكفاءة من محدث، الفلتر الغاني في الأداء الأمثل إلى الأعداء، التغييرات إلى سيطرة وتصنيف الساكنات الأسبق من دراساتexecution، وتم الانتهاء من الفحص.