EXTRACTION OF RETINAL BLOOD VESSEL BY COMBINING GABOR FILTER AND GENERALIZED LINEAR MODEL

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ABSTRACT

Here we are combining Gabor filter and Generalized Linear Model (GLM) for extraction of blood vessels of retina, with this use clarity in extraction can be improved. Since retina is a complex and delicate ocular structure, a huge effort in computer vision is devoted to study blood vessels network for helping the diagnosis of pathologies like diabetic retinopathy, hypertension retinopathy, retinopathy of prematurity or glaucoma. To carry out this process many works for normal and abnormal images have been proposed recently. These methods include combinations of algorithms like Gabor filters, histogram equalization, combined corner/edge detectors, neural networks, morphological operators etc. To apply these algorithms pre-processing tasks are needed. Most of these algorithms have been tested on publicly retinal databases. This paper presents a review of algorithms for detection of blood vessels by combining Gabor filter and generalized linear model from retinal images.

Keywords: Gabor Filter, Image Segmentation, Machine Learning, Vessels Extraction.

1. INTRODUCTION

Diabetic retinopathies, hypertension retinopathy, retinopathy of glaucoma are one of the major causes of blindness in the world. It occurs when diabetes affects the circulatory blood system of eye retina and damages the blood vessels in the retina which leads to partial or complete blindness. The effect of blood leakage from these vessels creates certain lesions in eye retina, e.g., Micro aneurysms, Hemorrhages, Neovascul-arisatio, hard exudates, Soft exudates, Cotton wool spots, and venous loops. Non proliferative DR (NPDR) and Proliferative DR (PDR) are two types of DR. Stages of DR can be classified as Mild NPDR, Moderate NPDR, Severe NPDR, and PDR [1].

Manual image segmentation of retinal blood vessels is a long and tedious task which also requires training and skill. It is commonly accepted by the medical community that automatic quantification of retinal vessels is the first step in the development of a computer-assisted diagnostic system for ophthalmic disorders. A large number of algorithms and techniques have been published relating to the detection of retinal blood vessels. Here we have surveyed of algorithms particularly focusing on the detection of blood vessels. The examination of the retinal images, generally do it with high definition ophthalmology camera, for example RetCam (Clarity Medical Systems Inc., Pleasanton, CA, USA)

The input for algorithms is fundus color images and the requirement is to be able to classify each pixel as vessel or non-vessel. For doing this complex task, researchers use and improve many algorithms like Gabor filter, histogram equalization, matched filter, combined corner/edge detector; neural network etc., some of them can be combined to get better results also improvements in analysis as well as predictions. There are cases where deterrotion may occur by doing this. Hence forth careful selection of methods for combination is required [2].

II PROCESSES

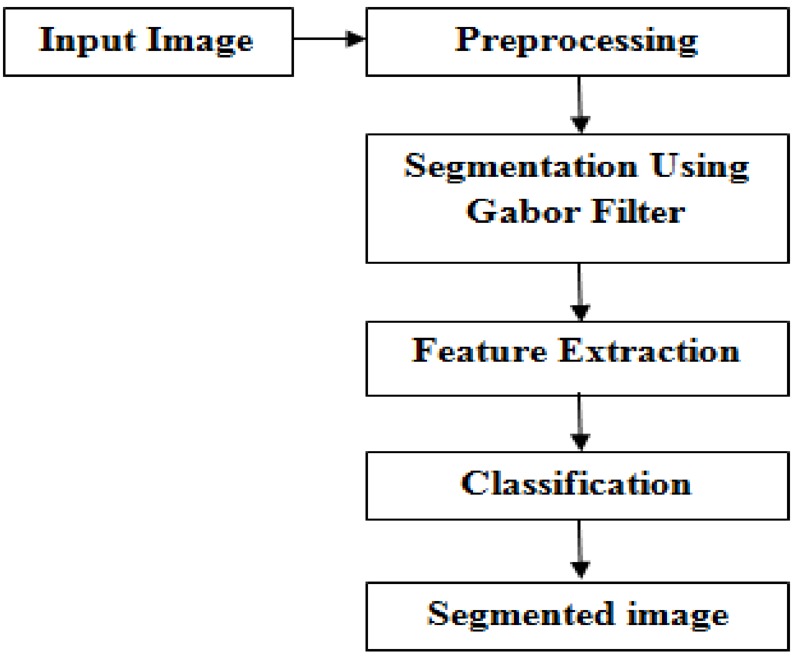
2.1 Retinal Photography

Retinal photography requires the use of a complex optical system, called a fundus camera. It is a specialized low power microscope with an attached camera, capable of simultaneously illuminating and imaging the retina. It is designed to image the interior surface of the eye, which includes the retina, optic disc, macula, and posterior pole. In Color photography the retina is examined in full color under the illumination of white light. In Red-free photography, the vessels and other structures are improved in contrast and the imaging light is filtered to remove the red colors. The fluorescent angiograms are acquired using the dye tracing method. A sodium fluorescein or indocyanine green is injected into the blood, and then the angiogram is obtained by photographing he fluorescence emitted after illumination of the retina with blue light at a wavelength of 490 nanometers [3].

2.2 Image Preprocessing

In order to remove the imperfections like lighting variations, poor contrast and noise, a preprocessing comprising the following steps is applied: vessel central light reflex removal, background homogenization, and vessel enhancement

BLOCK DIAGRAM



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2.2.1 Vessel Central Light Reflex Removal

Retinal blood vessels have lower reflectance; they appear darker than the background. In the vessel cross-sectional profile, some blood vessels include a light reflex which runs down the central length of the blood vessel. To remove this brighter strip, the green plane of the image is filtered by applying a morphological opening as shown in Fig. 1(b). Disc diameter was chosen as a minimum value to reduce the risk of merging close vessels. I_J denotes the resultant image for future references.

2.2.2 Background Homogenization

In fundus images background intensity variation is due to non uniform illumination. With the purpose of removing these background lightening variations, a shade-corrected image is accomplished from a background estimate. This image is obtained by applying a 3x3 mean filter and subsequently convolving the resultant image with a Gaussian kernel. A background image I_B , is produced by applying a 69x69 mean filter [Fig. 1(b)]. Then, the difference D between I_J and I_B is calculated for every pixel.

$$D(x,y)=I_y(x,y) - I_B(x,y)\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Finally, a shade-corrected image I_{SC} is obtained by transforming linearly values into integers covering the whole range of possible gray-levels ([0-255], referred to 8-bit images). Fig. 1(c) shows the corresponding to a no uniformly illuminated image. The proposed shade correction algorithm is observed to reduce background intensity variations and enhance contrast in relation to the original green channel image. Significant variation in image intensity is reduced by a homogenized image [Fig. 1(b)] produced as follows: the histogram of is displaced toward the middle of the grayscale by according to the following gray-level transformation function:

$$g_0=\begin{Bmatrix} 0 & if & g<0 \\ 255 & if & g<0 \\ g & otherwise & \end{Bmatrix}\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where $g=g_I+128-g_{IM}$

g_I and g_O are the gray-level variables of input and output images. The variable denoted by g_{IM} defines the gray-level presenting the highest number of pixels in g(x,y)

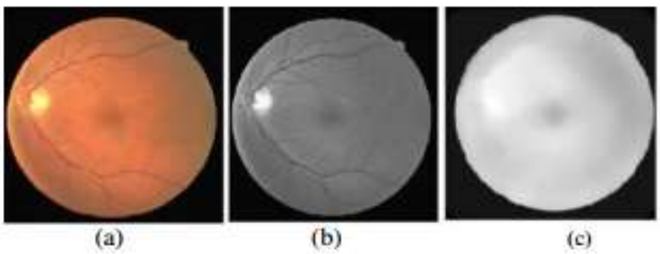
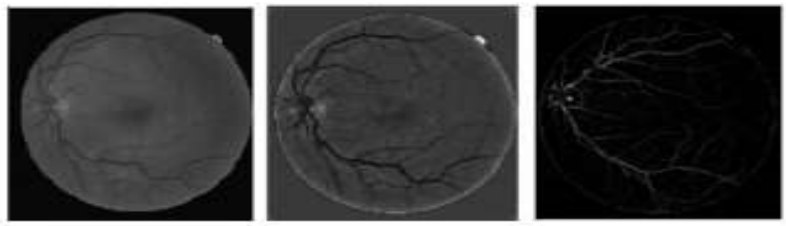


Fig: 1. Illustration of the preprocessing process: (a) RGB Image. (b) Green channel of the original image. (c) Background image.

By means of this operation, pixels which correspond to the background of the retina are set to 128 for 8-bit images. Fig. 2(b) shows this effect for fundus images in the STARE database.



(a) (b) (c)

Fig: 2. Application of the preprocessing with different illumination conditions. (a) Green channel of the original images.(b) Homogenized images. (c) Vessel-enhanced images.

2.2.3 Vessel Enhancement

The final preprocessing step consists on generating a new vessel-enhanced image, which proves more suitable for further extraction of moment invariants based features. Vessel enhancement is performed by estimating the complementary image of the homogenized image, and subsequently applying the morphological Top-Hattransformation[Fig.2(c)].

$$I_{VE}=I^{C}_{H} - \gamma\ (I^{C}_{H})……………(3)$$

where γ is a morphological opening operation using a disc of eight pixels in radius. Thus, while bright retinal structures are removed, the darker structures remaining after the opening operation become enhanced (i.e., blood vessels, fovea, possible presence of microaneurysms or hemorrhages).[4]

2.3 Retinal Vessel Segmentation

2.3.1 Pixel Processing Based Methods

The pixel based methods frequently use a two-step approach. The first step is an enhancement procedure, usually a convolution operator, with the main purpose of selecting an initial set of pixels to be further validated as vessels in the second step. The emphasis given to each one of these two phases justifies the subdivision proposed in several distinctive solutions are described in the literature for pixel processing-based methods. Matched filters method employs a two-dimensional linear structural element (kernel) that has a Gaussian cross-profile section, extruded or rotated into three dimensions to identify the cross-profile of the blood vessel, which typically has a Gaussian or a Gaussian derivative profile. The kernel is rotated into many different orientations (two or 12) to fit into vessels of different configuration. The images are then threshold (an arbitrary chosen grey level divides all features into a binary classification, depending on whether they have a greater or lesser intensity level than the „brightness threshold) to extract the vessel silhouette from the background. This works reasonably well on images of healthy retina. In diseased states such as diabetic retinopathy, there are problems associated with detecting very fine neovascularisation, partly due to image resolution and also smaller vessels are more prone to changes in background intensity and there is a reduced contrast-to-noise ratio. To overcome this, non-linear tram-line filters have been used, utilizing the contrast between central lines oriented along the vessel and satellite tram-lines at either side. However, using too long structuring element may have difficulty in fitting into highly tortuous vessels. Matched filters do not operate in isolation, but as part of an algorithmic chain, requiring thresholding into a binary vessel/non-vessel image. [4]

2.3.2 Gabor Filter

Gabor filters [6] have been used extensively by researchers for texture detection, classification and image retrieval purposes. The real part of 2D Gabor filter used in the context of retinal vessel segmentation is defined in the spatial domain g(x, y) as follows

$$g(x,y) = exp\left[-\pi\left(\frac{x_p{}^2}{\sigma_x}+\frac{y_p{}^2}{\sigma_y}\right)\right]\cos(2\pi f x_p)\ldots\ldots\ldots(4)$$

Where

$x_p = x\cos\theta + y\sin\theta$

$y_p = -x\sin\theta + y\cos\theta$

Where

θ=orientation of the filter

f=frequency of pass band

σ_x=standard deviation 0f Gaussian in x direction.

σ_y=standard deviation of Gaussian in y direction.

2.4 Feature Extraction

Many features such as colour, appearance, gist, location and texture can be extracted from superpixels for classification[9]. Here some features are below discussed.

2.4.1 Morphological Processing

The term mathematical morphology is used as a tool for extracting image components that are useful in the representation and description of region shapes such as features, boundaries. Morphological operators apply structuring elements (SE) to images, and are typically applied to binary images but can be extended to gray-level images. The two main morphological operators are dilation and erosion. Dilation expands objects by a defined Structuring Element, filling holes, and connecting the disjoint regions. Erosion shrinks the objects by a Structuring Element.

Morphological processing for identifying specific shapes has the advantage of speed and noise resistance. The main disadvantage of exclusively relying upon morphological methods is that they do not exploit the known vessel cross-sectional shape. In addition the use of an overly long structuring element may cause difficulty in fitting to highly tortuous vessels [3]

2.5. Classification of Retinal Vessel Segmentation

A classification procedure assigns one of the classes (vessel) or (nonvessel) to each candidate pixel when its representation is known. In order to select a suitable classifier, the distribution of the training set data in the feature space was analyzed and it shows that the use of a non linear classifier was necessary.

In this generalized linear model, the signal flows from the input unit to the output unit in a forward direction. This is useful over single layer net in the sense that, it can be used to solve more complicated problems.

The bright pixels in this image indicate higher probability of being vessel pixel. In order to get a vessel binary segmentation, a thresholding structure on the probability map is used to decide whether a particular pixel is part of a vessel or not. Therefore, the classification procedure allots one of the classes C1 or C2 to each candidate pixel, depending on if its associated probability is greater than a threshold.

Some misclassified pixels looked as undesirable noise in the classified image. Moreover, for some vessels, only their boundaries were ordered, so that it was needed to do post processing by using morphological tools to obtain the final desired segmentation. Finally, to optimize the vessel contours, morphological operations have been applied, beginning by area open to eliminate small noisy components.

2.5.1 Generalized Linear Model

Generalized Linear Model is nothing but a Extreme Learning Machine approach.ELM parameters can be analytically determined rather than being tuned. This algorithm provides good generalization performance at very fast learning speed. From function approximation point of view ELM [7] is very different compared to the traditional methods. ELM shows that the hidden node parameters can be completely independent from the training data.ELM meant for Single Hidden Layer Feed-Forward Neural Networks (SLFNs) will randomly select the input weights and analytically determines the output weights of SLFNs. This algorithm tends to afford the best generalization performance at extremely fast learning speed. The structure of ELM network contains an input layer, hidden layer and an output layer.

Extreme Learning Machine Training Algorithm

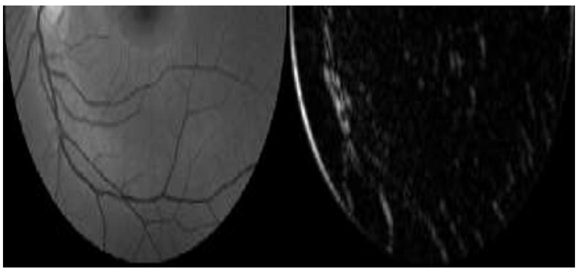
The ELM algorithm works as follows:

Given a training set N, activation function g(x) and hidden neuron $\tilde{N}$, Assign random value to the input weight w_i and the bias b_i , i=1,.. $\tilde{N}$. Find the hidden layer output matrix H. Then find the output weight β,using $\hat{\beta}=H^{+}T$ where β , H and T are defined in the same way they were defined in the SLFN[4].

III EXPERIMENTAL RESULTS

3.1 Feature Extraction

The acquired image is subjected to training and testing.These processes carryout for half of the images.The next step is to perform Gabor transforms with varying Gabor filters to the training image, and the transformed images as features. Gabor filter is used for edge detection.Here first initialize the parameters for gabor transform like the shape of the filter can be varied by altering layer and an output layer.The size of the envelope with 'sigma',the direction of the sinusoid with 'theta' and frequency of the sinusoid with 'F'.



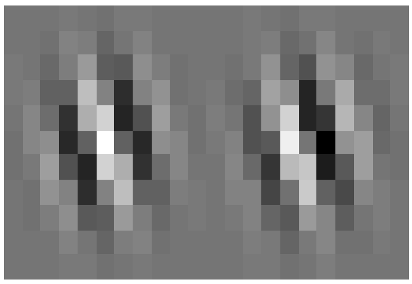


Fig: 3(a) Testing image and Gabor transformed image **(b) Gabor filter F:0.30 t:2.75 k:2**

3.2 Fit GLM with features and location of vessels

Now the generation of GLM using the features extracted above and also location of the vessels in the training image carried out.

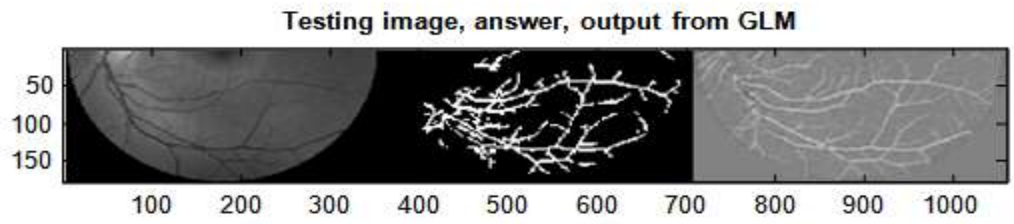


Fig4: a) testing image b) Gabor output c) output from GLM

The above figure shows the testing image and the output image can be observed from the generalized learning features

3.3 Receiver Operating Characteristics

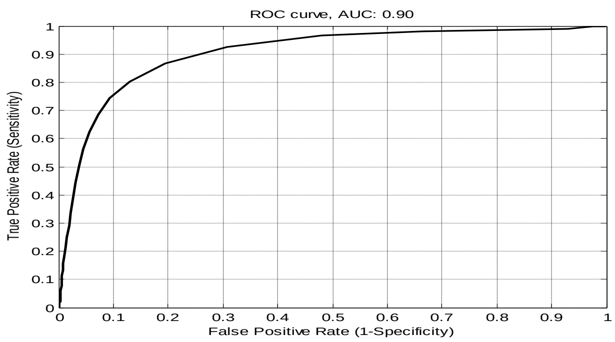


Fig 5: ROC curve

The curve shows the Receiver Operating Characteristics (ROC) curve shows the true positive rate versus false positive rate (equivalently, sensitivity versus 1–specificity) for different thresholds of the classifier output and also shows the Area Under the Curve (AUC).

Sensitivity gives the percentage of pixels correctly classified as vessels and specificity gives the percentage of non-vessels pixels classified as non-vessels.

3.4 Output

The below figure shows the original image ,GLM output and Thresholded output from GLM.

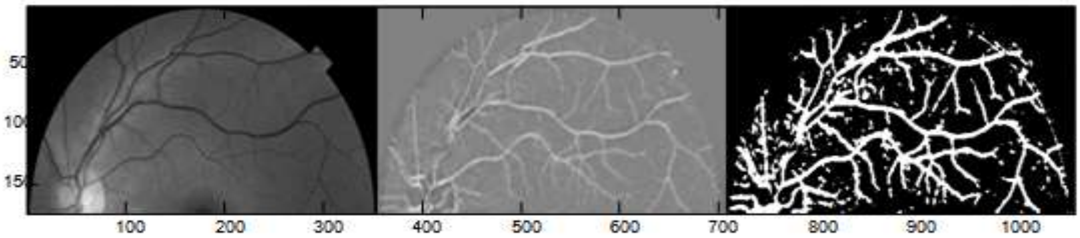


Fig 6: A) Original Image B) Output from GLM C) Thresholded Output from GLM

As you can see from the ROC curve, by training half of the retinal image, the proposed method is able to detect the other half of the image with satisfactory performance (area under the curve of 0.90).

3.5 Tabular column

Method	Sensitivity	Specificity
1.FUZZY[8]	60.42	25
2.ANFIS[8]	60.42	25
3.GENERALIZED LINEAR MODEL(GLM)	60.52	48.88

On observation the values of sensitivity & specificity are improved when compared to the values obtained inFUZZY[8] &ANFIS[8].

Proposed algorithm was evaluated in terms of sensitivity (Se), specificity (Sp).Assume TP and TN show the blood vessel pixels and background pixels which correctly detected, respectively. FP shows the pixels not belonging to a vessel but recognized as blood vessel pixels and FN shows the pixels belonging to a vessel but recognized as background pixels, mistakenly.

$$S_e = \frac{TP}{TP+FN}$$

$$S_e = \frac{TN}{TN+FP}$$

IV CONCLUSION

This method presents a new supervised technique for blood vessel extraction in digital retinal images. This novel approach uses a Generalized Linear Model (GLM) approach for pixel classification. The performance of the proposed approach is evaluated on the DRIVE and STARE databases. It is observed that the proposed approach provides significant.

V ACKNOWLEDGEMENT

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