International Journal of Emerging Engineering Research and Technology

Volume 2, Issue 2, May 2014, PP 119-125

Segmentation of Retinal Vessels by the Use of Gabor Wavelet and Linear Mean Squared Error Classifier

Hemant P. Chaudhari
AISSMS Institute of Information Technology,
University of Pune, Pune

Amol D. Rahulkar
AISSMS Institute of Information Technology,
University of Pune, Pune

Chetankumar Y. Patil
College of Engineering, Pune.

Abstract: *This paper presents a method to segment the retinal vessels using multi-scale, multi-directional Gabor wavelet and supervised classifier. This method obtains the retinal vascular segmentation by classifying each image pixel as vessel or non-vessel based on the feature vector. In this method, 2-D anisotropic Gabor wavelet is tuned at specific frequency in order to derive the feature vector. This feature vector consists of the pixel's intensity values of the retinal image and the maximum response of Gabor wavelet chosen at different scales. With this, noise filtering and vessels enhancement have been obtained in a single step. Next, in order to improve the result, supervised classifier named as linear minimum squared error (LMSE) classifier is used to classify the blood vessels as a vessels or non-vessels. The performance of the proposed method is evaluated using two databases namely DRIVE and STARE. The experimental results gives an accuracy of 86.79% and 87.23% for DRIVE and STARE databases respectively.*

1. INTRODUCTION

Diabetic Retinopathy is the disease of retina due to diabetes. Diabetes Mellitus is the inability of the body to use and store sugar properly, resulting in high blood sugar levels. This disease has many adverse effects on the eyes, nervous system, heart, kidneys and other organs, but the most likely to be affected first is the retina, hence the patient' sight. The blood vessels bring oxygen and nourish the retina. These blood vessels may get damaged in a number of ways if you have diabetes. If blood vessels of retina get damaged, patient may get distorted eye sight or total loss of vision. This disease is called Diabetic Retinopathy (DR). DR is a progressive eye disease cause due to increase of insulin in blood and can cause blindness if not detected timely. Guariquata *et al.* [1] had a survey on the percentage of diabetes and concluded that diabetes is increasing day by day. In 2010, it was 6.5% and in 2011 it was 7.1%.

A number of methods have been proposed for blood vessel detection and segmentation, but detection of neovascularization is still a difficult problem [2]. Soares *et al.* [2] proposed a retinal vessel segmentation by the use of Gabor wavelet and Gaussian mixture model supervised classifier to classify the image pixel as vessel or non-vessel. Wang *et al.*[3] obtains the region of interest from retinal images and select the green band of retinal images as given in [2]. The next step is to perform illumination equalization. The authors introduced the matched filters by the use of 12-Gaussian filters for feature extraction on a preprocessed retinal image. The feature points are extracted from the matched filter response (MFR) image which is used as starting points for iterative adaptive local threshold probing. Akram *et al.* [4] proposed a method to detect abnormal blood vessels and grading of proliferative diabetic retinopathy by multivariable m-Mediods based classifier. Ramlugun *et al.* [5] presented an algorithm to extract the smallest retinal vessels from the input image. In their method, contrast limited adaptive histogram equalization (CLAHE) is used for the enhancement of the retinal vasculature adaptively. Kharghanian and Ahmadyfard [6] has described the blood vessel segmentation using Gabor wavelet and line operator where preprocessing is performed on the green channel image. Next, Bayesian and support vector machine (SVM) are used to classify the blood vessels. Abbadi and Saadi [7] proposed a hybrid method to extract the blood vessels by the combination of top-hat transformation, opening by reconstruction, opening-closing by reconstruction, erosion, dilation and watershed algorithm. Mendonka and Campilho [8] presented a method for segmentation of retinal

blood vessels by combining the detection of centerlines and morphological reconstruction. The preprocessing consists of background normalization and thin vessel enhancement. To improve the discrimination between these thin vessels and the background noise, the normalized image is processed with a set of line detection filters corresponding to the four orientations 0 , 45 , 90 , and 135 . Next, a set of directional filters known as difference of offset Gaussians filters (DoOG filters) are applied on the preprocesses image to extract the retinal features. Rattathanapad *et al.*[9] developed an algorithm using Gaussian kernel and hessian matrix to extract the blood vessels. Chaudhari *et al.* [10] suggested a 2-D linear kernel with a Gaussian profile for segmentation of the retinal vessels. Xu and Luo [11] presented a method for blood vessel detection from retinal image. based on the combination of wavelet and curvelet transform. Staal *et al.* [12] suggested the primitive-based method that uses image primitives formed from image ridges that approximates the straight line elements. Next, the k-Nearest neighborhood (kNN)-classifier is used to classify the feature vectors. Marín *et al.* [13] proposed a supervised approach based on NN using gray level and moment invariant-based features. Ricci and Perfetti [14] presented retinal blood vessels segmentation using line operators and support vector classification. The detail literature survey on retinal blood vessel segmentation can be found in [15].

This paper presents an approach to construct the feature vector by the concatenation of each image pixel and the maximum response of Gabor wavelet as given in [2]. The resulting feature space is used to classify each pixel as either vessel or non-vessel pixel by the use of linear minimum squared error classifier.

The rest of the paper is organized as follows. Section 2 presents the image preprocessing steps requires for the feature extraction from the retinal images. The construction of feature vector is explained in Section 3. Section 4 describes the supervised classifier to classify the image pixels as vessels or non-vessels. Section 5 gives the experimental results followed by conclusion in Section 6.

2. RETINAL IMAGE PRE-PROCESSING

The general block diagram of the implemented method is shown in Fig. 1. The first step is to acquire the retinal fundus image. The second step is to apply the preprocessing algorithms in order to remove pathological noise and reduce the false detection of border of the camera'a aperture. Next, the feature extraction tool is used to detect and analyze the localized properties and singularity (blood vessels). The classifier is needed at the last to classify every pixel in an image as vessel or non-vessel.

The preprocessing algorithm consists of selection of green channel intensity image, enhancement of the region of interest (ROI) that is inside the camera's aperture.

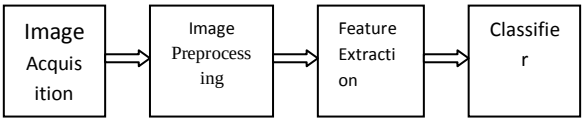


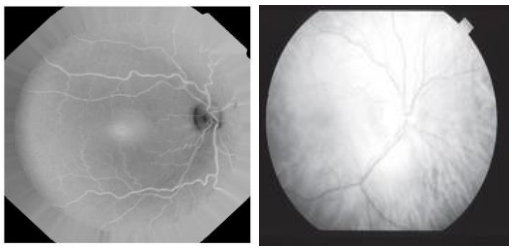
Fig.1. *Block diagram of the retinal vessel segmentation.*

2.1 Selection of Green Channel Image

The preprocessing of digital fundus image is a major issue in automatic screening systems for diabetic retinopathy [2]. The digital fundus images are more appropriate for automatic screening systems. Unfortunately, a significant percentage of these images is of poor quality that hinders further analysis due to many factors such as patient movement, poor focus, or inadequate illumination [2]. The captured digital image is the colour image which consists of red, green and blue components. It is observed that the green channel component shows the best vessel/background contrast as shown in Fig.2 (a), whereas, red and blue channels show low contrast and are very noisy. Therefore, green channel is selected for the feature selection.

2.2 Mask Generation

The preprocessing is for instance the generation of a mask image to determine which area belongs to the actual fundus and background of the image. It is important to separate the fundus from its background so that the further processing is only performed for the fundus and not interfered by pixels belonging to the background. For the creation of mask image, we have considered the red channel of the image as shown in Fig. 2 (b), as it has low contrast hence it becomes easy for the mask image creation. However, this image is having variations in intensity level which needs to be normalized in the range of 0 and 1. Therefore, normalization is carried out by dividing each pixel value by 255 i.e. maximum intensity values.

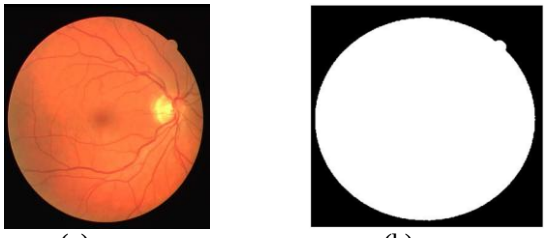


(a) **(b)**

Fig.2(a) *Green channel and Fig. 2(b) Red Channel image*

2.3 Edge Detection

The Edges characterize boundaries and are therefore a problem of fundamental importance in image processing. Image Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. In this method, LoG is used to obtain the edges. After the determination of edges, the missing parts in the edges are filled by selection of optimum threshold value. By removing the objects smaller than the threshold value, seed image is created. In order to create the mask image take away this seed image from the border and fills the seed until it reaches the edges of the aperture. A median filter of size 3×3 is used to remove any noise from the created fundus mask and the edge pixels are removed by morphological erosion with a structuring element of size 5×5. The quality of mask image is improved by removing the false positive countour and other false positives. The colored original image and good quality mask image are shown in Fig. 3 (a)-(b).



(a) (b)

Fig. 3 (a) *Coloured input image (b) Mask image*

2.4 Region of Interest (ROI)

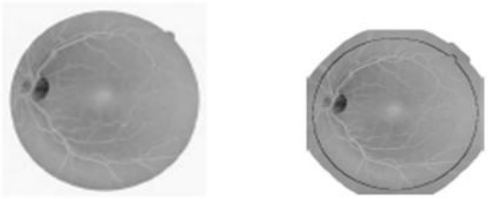
Our interest is to remove the strong contrast between the retinal fundus and the region outside the aperture. The algorithm for the artificial extension starts from the ROI is as follows:

1)Initially, determined the pixels outside the aperture that are neighbors to pixels inside the aperture.

2) Replace each value of the exterior pixels values with the mean value of their neighbor pixels inside the aperture.

3) Finally, the ROI is expanded by inclusion of this altered set of pixels.

4) This process is repeated and it is seen as artificially increasing the area inside the aperture shown in Fig. 4 (a)-(b).



(a) (b)

Fig.4. (a) *Green channel image (b) Extended border image.*

Next, the original color image is multiplied with the created mask image results in a colour image without noisy pixels in the background, while the ROI is left unchanged.

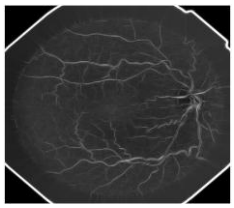


Fig. 5. *Inverted green channel image*

3. CONSTRUCTION OF FEATURE VECTOR

The image pixel of a fundus image can be viewed as object that represented by feature vector so that we can apply statistical classifier to segment the image [2]. In this case, two classes are considered named as vessels and non-vessel pixels. The training set for the classifier is derived by manual segmentation of training images. This approach allows us to integrate information from Gabor wavelet responses at multiple scales to distinguish pixel from each class.

Before the application of the Gabor wavelet to non-mydriatic images, the green channel of the image is inverted to appear vessels brighter than the background as shown in Fig. 5. The retina is a vascular structure and having distribution of blood vessels, any abnormality indicates change in blood vessel distribution. Hence it is important to enhance all vessels. In this paper, we have used Gabor Wavelet [2] to enhance thick and thin vessels. The problem with blood vessel segmentation is that the visibility of

vascular pattern is usually not good especially for thin vessels. So, it is necessary to enhance the vascular pattern. Normally matched filters [10] (MFs) are used for blood vessel enhancement but the drawback is that MFs not only enhance blood vessels edges they also enhance bright lesions. On the other hand, Gabor wavelets [2] can be tuned for specific frequencies and orientations which is useful for both thick and thin vessels. Also, since vessels have directional pattern so 2-D Gabor wavelet [2] is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies. The detail on the design of Gabor wavelet is found in [2]. The Gabor wavelet is the modulation of Gaussian function with complex sinusoid and given as:

$$\Psi_G(x)=\exp(jk_0x)\exp(-½|Ax|^2) \quad (1)$$

Where A = diag $[\varepsilon^{-½}, 1]$, $\varepsilon \geq 1$ is a 2 x 2 positive definite matrix that defines the anisotropy of the filter, it means elongation of filter at any desired direction. k_0 is a vector that defines the frequency of the complex exponential.

For each orientation (i.e. pixels position) and different scale values, we are interested in the response with maximum modulus and is expressed as:

$$M_\psi(b,a)=\max|T\psi(b,\theta,a)| \quad (2)$$

where $T\psi$ is the Gabor wavelet at particular scale and orientation. With this, these maximum values were taken as the main components of the pixel feature vectors. Thus, the feature vectors composed of the pixel's intensity values and 2-D Gabor wavelet transform responses taken at multiple scales. The Fig. 6 shows the maximum modulus of the Gabor wavelet transform over angles for scale value at $a = 4$

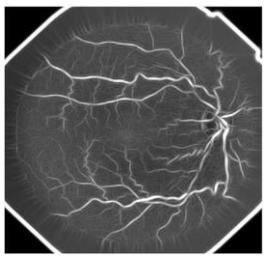


Fig.6. *Maximum modulus of the Gabor wavelet transform over angles, Mψ(b,a) for scale values at a = 4.*

Next, these features must be labeled in terms of vessels and non-vessels. To label each pixel as vessel and non-vessel, we have considered mid value 128 as a threshold value. If the pixel intensity is greater than 128 then the pixel is taken as vessel and if pixel intensity is less than or equal to 128 then the pixel is non-vessel. The labeled matrix is added to features space. These features are arranged in matrix form taking only pixels from ROI. One matrix is created consisting of all ones equal to the size of feature matrix. This matrix is convolved with the mask image to get a complete feature matrix. Then we have calculated the total number of vessel pixels and total number of non-vessel pixels by creating vesselmatrix and restmatrix (i.e. non-vesselmatrix). The features extracted from each image must be normalized separately in order to compensate the inherent variation among images. Therefore, normal transformation is applied separately to each image's feature space by its own means and standard deviations [2], helping to compensate for intrinsic variation between images, such as global illumination variation.

4. SUPERVISED PIXEL CLASSIFICATION

After feature generation and normalization, supervised classification has been applied as given in [2] to obtain the final segmentation, with the pixels classified as C_1 and C_2 as vessel pixels and non-vessel pixels, respectively. Several fundus images have been manually segmented to obtain the training set. This allows the creation of a labeled training set into classes C_1 and C_2. Due to the computational cost of training the classifiers and the large number of samples, randomly we have selected a subset of the available samples to use for actually training the classifier. Soares *et al.* [2] have been used Gaussian mixture model for the supervised classification. However, the computational time for the training is high. In order to reduce the computational time, the linear minimum squared error (LMSE) classifier is used to classify the pixels as vessels or non-vessels and is defined by a linear decision function g in the d-dimensional feature space [16]

$$g(v)=w^tv+w_0 \quad (3)$$

Where, w is the weight vector, v feature vector, w_0 threshold. A linear discriminant function for the two-category classifier is defined as

$v = [1; v_1, \ldots. v_N]^t = [1;v]^t$; and the augmented weight vector as: $w = [w_0; w_1; \ldots.; w_N]^t = [w_0;w]^t$:

In order to simplify the formulation, the threshold value w_0 is accommodated with the weight vector and hence the feature vector has to be extended by (d+1) dimensional vector. The

generalized linear discriminant function yields the following homogeneous form:

$$g(v)=w^t v \quad (4)$$

Based on (4), the classification rule is to decide C_1 if $g(v)>0$ otherwise C_2,where, C_1= Vessels and C_2 = Non-vessels.

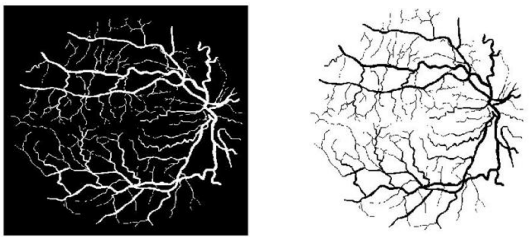
Assume, we have a set of n samples v_1; .... v_N, some labeled $w1$ and some labeled $w2$. We want to use these samples to determine the weights w in a linear discriminant function $g(x) = w^t v$. Suppose we have reason to believe that there exists a solution for which the probability of error is very low. Then a reasonable approach is to look for a weight vector that classifies all of the samples correctly. If such a weight vector exists, the samples are said to be linearly separable.

With the tools of matrix derivatives, let us now proceed to find in closed-form the value of w that minimizes J(w). The LMSE classifier is determined by finding w that minimizes the sum of squared error criterion as given by (5) and expressed as:

$$J(w) = \sum_{i=1}^{N} (y_i - v_i{}^T w)^2 \quad (5)$$

Where, N is the total number of training samples, v_i is the extended i^{th} training sample and y_i is desired output.

The result of image segmentation is a set of segments that collectively cover the entire image. Each of the pixels in a region are characterized or computed on the basis of its intensity, as adjustment region are significantly different with respect to the same characteristics. The output of LMSE Classifier that is obtained is as shown in Fig. 7 (a)-(b). Fig. 7 (a) represents the segmented vessels image where as Fig. 7(b) indicates the segmented non-vessels image in the retinal image.



(a) (b)

Fig. 7. *Classifier results (a) vessels (b) non-vessels*

5. EXPERIMENTAL RESULTS

There are various publicly available databases of non-mydriatic images for diabetic retinopathy such as DRIVE [17], STARE[18], MESSIDOR[19], ARIA [20] along with corresponding manual segmentations. The proposed method has been tested on colored non-mydriatic images i.e. DRIVE (Digital Retinal Images for Vessel Extraction) and STARE (Structure Analysis of the Retina) databases.

The DRIVE database consists of 40 images along with manual segmentations of the vessels. The images are captured in digital form from a Canon CR5 non-mydriatic 3CCD (Three Charge-Coupled Device) camera at 45° field of view. These 40 images are divided into a training and testing set, each containing 20 images. The size of the images is 768 X 584 pixels with 8 bits/color channel. FOV is approximately 540 pixels in diameter.

The STARE database consists of 20 digitized images especially for blood vessel segmentation. These images are captured by a TopCon TRV-50 fundus camera at 35° field of view. The size of the images is 700 X 605 pixels with 8 bits/color channel. FOV is approximately 650 X 540 pixels in diameter. Two observers have manually segmented all images. The segmentations of the two observers are fairly different in that the second observer segmented thinner vessels than the first observer.

The inverted green channel image is considered as input image. Next, the Gabor wavelet with three scales 2, 3, and 4 are applied on this inverted green channel image. In order to tune the Gabor parameters, the values of elongation parameter $\varepsilon = 4$ and k_0=[0,3] are selected i.e. a low frequency complex exponential with a few significant oscillations perpendicular to the large axis of the wavelet where we get the optimum performance. Both these characteristics are primarily suited for the detection of directional features. These are chosen in order to enable the transform to present stronger responses for pixels associated with the blood vessels.

In this way, the Gabor wavelet transform is computed for θ (orientation) spanning from 0° up to 170° at steps of 10° and the maximum is considered

(i.e. 18 orientations) [2]. The response of such a filter bank to an input image is a set of filtered images. In fact, for each considered set of frequency and scale parameters, we were interested in the Gabor filter response with the maximum value over all possible orientations.

Feature Vectors	DRIVE	STARE
	Avg. Accuracy (%)	Avg. Accuracy (%)
Green channel intensity+ 1 Gabor responses	86.79	87.21
Green channel intensity+ 2 Gabor responses	86.64	87.18
Green channel intensity+ 3 Gabor responses	86.79	87.23

In the first set of experimentation, the LMSE classifier is trained with two different feature vectors i.e. inverted green channel intensity values and Gabor wavelet response for one scale. The second set of experimentation is carried for three feature vectors i.e. inverted green channel intensity values and Gabor response for two scales. At the last, the LMSE classifier trained with four different feature vectors i.e. intensity values and Gabor response at three scales.

For the DRIVE database, the training set was formed by pixel samples from the 20 labeled training images. For the STARE database, leave-one–out tests were performed i.e. every image is segmented using samples from the other 19 images for the training set. Because of the large number of pixels in all experiments, one million pixel samples were randomly chosen to train the classifiers. The tests were performed with the LMSE classifier to classify the retinal vessels as vessel or non-vessel. The proposed method is validated by measuring the classification accuracy. The classification accuracy is defined as the ratio of the number of correctly classified pixels by the total number of pixels in the image.

The average classification accuracies for different feature vectors for DRIVE and STARE databases are shown in Table 1. It is observed that the proposed scheme achieves the 86.79% and 87.23% accuracies for DRIVE and STARE databases respectively.

6. CONCLUSIONS

This paper presents the retinal vessel segmentation approach based on the combination of Gabor wavelet, inverted green channel intensity, and LMSE classifier. The feature vector is derived by the combination of green channel intensity values and Gabor responses at different scales. It is observed that Gabor wavelet is efficient in enhancing vessel contrast, while filtering out noise. The LMSE classifier shows a reasonable performance with a fast classification and training phase.

Table.3.1. *Average classification accuracies for DRIVE and STARE databases*

REFERENCES

[1] Whiting DR, Guariquata L, Weil C, Shaw J, "Global estimate of prevalence of diabetes for 2011 and 2030", Diabetes Research and Clinical practice, 87 (2010), pp4-14.

[2] J. V.B. Soares, J. J.G.Leandro, R. M.Cesar , H. F. Jelinek and M. J. Cree " Retinal Vessel Segmentation Using the 2-D Gabor Wavelet and Supervised Classification" , IEEE Transactions on Medical Imaging, vol.25, No.9, pp.1214-1222, 2006.

[3] Y. Wang, H. Lu, M. Xu and J. Zhang, "Detection of Blood Vessels in Retinal Images Using Improved Iterative threshold Probing of a Matched Filter Response", Proc. at Inter. Conf. on IFMBE, vol. 19, pp.241-244, 2008.

[4] M. Usman Akram, Shehzad Khalid, Anam Tariq, and M. Younus Javed, " Detection of neovascularization in retinal images using multivariate m-Methods based classifier", Elsevier, Computerized medical imaging and graphics (In Press), 2013.

[5] G. S. Ramlugun, V. K. Nagarajan, and Chandan Chakraborty., "Small Retinal Vessels Extraction towards Proliferative Diabetic Retinopathy Screening", Expert Systems with Applications (in press)Elsevier, 2011.

[6] R. Kharghanian and A. Ahmadyfard, "Retinal Blood Vessel Segmentation Using Gabor Wavelet and Line Operator", International Journal of Machine Learning and Computing, Vol. 2, No. 5, pp.593-597, 2012.

[7] N. K. Abbadi and E. H. Saadi, "Blood Vessels Extraction Using Mathematical Morphology", Journal of Computer Science, Vol. 9, No. 10, pp. 1389-1395, 2013.

[8] A. M. Mendonça and A. Campilho, "Segmentation of Retinal Blood Vessels b Combining the Detection of Centerlines and Morphological Reconstruction",IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp.1200-1213, 2006.

[9] S. Rattathanapad, P, Mittrapiyanuruk, P. Kaewtrakulpong, B. Uyyanonvara and C. Sinthanayothin, "Vessel Extraction in Retinal Images using Multilevel Line Detection", Proc. of the IEEE-EMBS International Conference on Biomedical and Health Information, pp. 345-349, 2012.

[10] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters", IEEE Trans. On Med. Imaging, vol. 8, no. 3, pp. 263-269, 1989.

[11] L. Xu and S. Luo, "A novel method for blood vessel detection from retinal images" , BioMedical Engineering OnLine, 2010.

[12] J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. Ginneken, "Ridge-Based Vessel Segmentation in Color Images of the Retina", IEEE Transactions on Medical Imaging, vol. 23, no. 4, pp. 501-509, 2004.

[13] D. Marín, A. Aquino, M. E. Gegúndez-Arias, and J. M. Bravo, "A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray-Level and Moment Invariants-Based Features", IEEE Transactions on Medical Imaging, pp.1-13,2010.

[14] E. Ricci and R. Perfetti, "Retinal blood vessel segmentation using line operators and support vector classification", IEEE Trans. On Medical Imaging, vol. 26, no. 10, 2007.

[15] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R.Rudnicka, C. G. Owen, S. A. Barman, "Blood vessel segmentation methodologies in retinal image- A survey", Elsevier, Computer methods and programs in medicine, vol. 8, pp. 407-433, 2012.

[16] R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification. John Wiley and Sons, 2001.

[17] [Availableonline] http://www.isi.u.nl/Research/Databases/Drive, 2004.

[18] A. D. Hoover, V. Kouznetsova, M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response", IEEE Transactions on Medical Imaging, vol. 19, pp. 203-210, 2000.

[19] [Availableonline],http://messidor.crihan.fr/index-en.php, 2004.

[20] [Availableonline],http://www.eyecharity.com/aria.online/,2006