ON RETINAL BLOOD VESSEL EXTRACTION USING CURVELET TRANSFORM AND DIFFERENTIAL EVOLUTION BASED MAXIMUM FUZZY ENTROPY

Sudeshna Sil Kar, Santi P. Maity

Department of Information Technology
Indian Inst. of Engg. Sc. and Tech., Shibpur
Howrah 711103, WB, INDIA
sudeshna.sil@gmail.com,
santipmaity@it.becs.ac.in

Claude Delpha

Laboratoire des Signaux et Systemes
CNRS, Universite Paris-Sud
Supelec-3, rue Joliot-Curie 91192, France
claude.delpha@lss.supelec.fr

ABSTRACT

This paper proposes a new method based on multiple thresholds for automatic extraction of blood vessels specially from a low contrast and non-uniformly illuminated background of retina. Curvelet transform is used to extract the finest details along the vessels since it can represent the lines, the edges and the curvatures very well. Next matched filtering is done to intensify the blood vessels' response in the enhanced image. The multiple threshold values for the maximum matched filter response that maximize the fuzzy entropy are considered to be the optimal thresholds to extract the different types of vessel silhouettes from the background. Differential Evolution algorithm is used to specify the optimal combination of the fuzzy parameters. Performance is evaluated on publicly available DRIVE database and is compared with the existing blood vessel extraction methods. Simulation results demonstrate that the proposed method outperforms the existing methods in detecting the long and the thick as well as the short and the thin vessels.

Index Terms— Retinal vessel segmentation, Curvelet, Matched filter, Fuzzy Entropy, Differential Evolution

1. INTRODUCTION

Proliferative diabetic retinopathy (PDR) is a common complication of diabetes. The fragile and the abnormal blood vessels that grow along the retina in PDR frequently cause minor bleeding, sometimes also lead to permanent vision loss. Existing retinal screening programs mostly employ manual extraction of blood vessels which is time consuming and prone to errors. Therefore, design of an automated system capable of accurate detection of blood vessels is very much necessary for the diagnosis and treatment of PDR. The existing methods of vessel segmentation are mainly based on pixel based classification techniques using artificial neural network [1], mathematical morphology [2], vessel tracking/ tracing [3], matched filtering [4] etc. A detailed description of these methods can be found in [5].

Retinal images are rich with thick and thin as well as small and large vessels. The vessels become thinner as they travel radially outward from the optic disc at different orientations. Moreover, the contrast between the background and the vessels becomes very poor. The images are also degraded during acquisition due to noise, blurring etc. and sometimes they are non-uniformly illuminated. Therefore, some kind of preprocessing is necessary before the segmentation operation is applied on the retinal images.

In this paper, curvelet transform is used for edge enhancement since it is very much efficient in identifying curves, contours, missing and imprecise edges, curvatures and other boundary information. Moreover, being a member of wavelet family, it offers multiresolution, space-frequency localization ability, very high directional sensitivity and anisotropy in frequency domain. After enhancing the image in the curvelet domain, matched filter with proper Gaussian profile is applied in the spatial domain to intensify the response against the various types of blood vessels. The extraction of the different types of vessel silhouettes from the background basically involves automatic selection of robust and optimal thresholds. To obtain the optimal threshold values, the fuzzy entropy function corresponding to the maximum matched filter response (MFR) is maximized. This requires an optimal combination of a set of fuzzy parameters. Differential Evolution (DE), a population based global optimization algorithm, is used to obtain the optimal combination of the fuzzy parameters.

The rest of the paper is organized as follows. Proposed method of vessel detection is described in Section 2. Section 3 reports the simulation results and discussions while conclusions and future works are mentioned in Section 4.

2. PROPOSED METHOD

The proposed method for retinal blood vessel extraction is diagrammatically represented in Fig 1. The entire methodology can be divided into the following five steps.

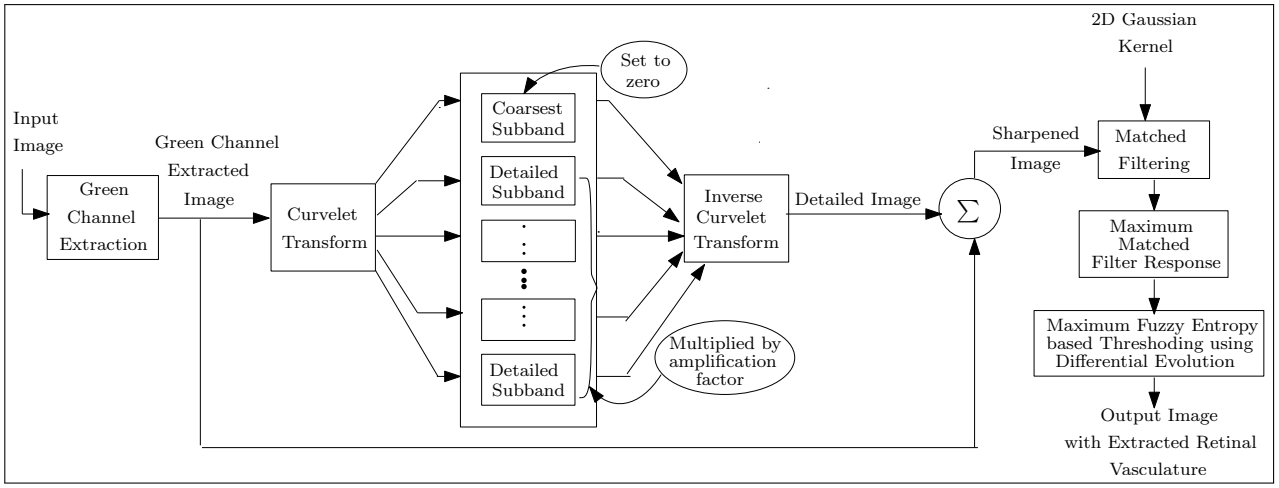

Fig. 1: Schematic Diagram of Proposed Method for Retinal Vessel Detection

Step 1: Green Channel Extraction

In this work, the green color plane is used for vessel extraction since the contrast between the blood vessels and the background is the maximum for this green channel [6].

Step 2: Curvelet based Edge Enhancement

To enhance the edges of the blood vessels first the image is decomposed into a number of subbands using curvelet transform with different scales and orientations. Curvelet co-efficients contain the most important information like the missing and the broken boundary information, horizontal, vertical, diagonal edge details as well as the coarse approximation of the image. Next the approximate subband i.e. the co-efficients corresponding to the coarse approximation of the image are set to zero and the detailed subbands are intensified multiplying by proper amplification factor. As a result, the background gets suppressed, while the detail edges are highlighted. After that the inverse curvelet transform on the background suppressed image is done and is superimposed on the original image. This in turn increases the contrast, specially between thin, tiny, faint vessels and the background. Thus, using curvelet transform both the strongest and the finest edges in the retinal image can be enhanced.

Step 3: Matched Filtering using 2D kernel

The grey-level profiles of the cross-section of blood vessels in retinal images are Gaussian in nature and the intensity profile is symmetric about the straight line that passes through the center of the vessel [4]. A two dimensional prototype matched filter kernel may be mathematically expressed as: $K(x,y) = -exp(x^2/2\sigma^2)$ for $|x| \leq (3\sigma)$ and $|y| \leq (L/2)$, where L is the length of the blood vessel segment considered to have fixed orientation and σ denotes the scale of the Gaussian function. Here the $-$ve sign implies the fact that the background is brighter than the vessels.

In an image, a particular vessel may be oriented at any angle between 0 and π and if the vessel is aligned at $\pi/2$, then only the matched filter will have its peak response. The filter is rotated at an increment of 12^0 and is convolved with the image under consideration. From the set of MFR, for each pixel, only the maximum one is retained.

Step 4: Maximum Fuzzy Entropy for Probability Partition

Fuzzy entropy describes the fuzziness of a fuzzy set. It is the basic concept in fuzzy set theory and is used widely in image processing for multilevel thresholding [7]. It is defined using the concept of membership function. Since the cross-section of the retinal vessels is Gaussian in nature, the MFR is the highest for the vessels and the lowest for the non-vessels. Let the maximum MFR of each pixel forms a $M \times N$ matrix and $G = \{m, m+1, \ldots, 0, 1, \ldots, q-1, q\}$ is a set of integers where m and q represent the nearest integer values of the lowest and the highest maximum MFR, respectively.

A 4-level fuzzy entropy based segmentation method is used to classify the maximum MFR into 4 classes, namely non-vessel and thick vessels using $Z(k,a,b,c)$ and $S(k,a,b,c)$ functions, respectively and medium and thin vessels using $\prod(k,a,b,c)$ function as shown in Fig 2. The symbols a, b, c indicate the fuzzy function parameters. Considering the partition probability and conditional probability are equal for a particular region, the following equation can be derived:

$$p_{nv} = \sum_{k=m}^{q} p_k * \mu_{nv}(k) \tag{1}$$

Here p_k is the probability that the maximum MFR is equal to k and μ_{nv}, μ_{thin}, μ_{med}, μ_{thick} represent the membership functions for the non-vessel, the thin, the medium and the thick vessels, respectively. The probabilities p_{thin}, p_{med} and p_{thick} can also be expressed in the same ways. The membership functions can be mathematically represented as:

$$\mu_{nv}(k) = \begin{cases} 1 & k \leq a_1 \\ 1 - \dfrac{(k-a_1)^2}{(c_1-a_1)(b_1-a_1)} & a_1 \leq k \leq b_1 \\ \dfrac{(k-c_1)^2}{(c_1-a_1)(c_1-b_1)} & b_1 < k \leq c_1 \\ 0 & k > c_1 \end{cases} \tag{2}$$

$$\mu^{'}(k) = \begin{cases} 0 & k \le a_n \\ \dfrac{(k-a_n)^2}{(c_n-a_n)(b_n-a_n)} & a_n < k \le b_n \\ 1 - \dfrac{(k-c_n)^2}{(c_n-a_n)(c_n-b_n)} & b_n < k \le c_n \\ 1 & c_n < k \le a_{n+1} \\ 1 - \dfrac{(k-a_{n+1})^2}{(c_{n+1}-a_{n+1})(b_{n+1}-a_{n+1})} & a_{n+1} \le k < b_{n+1} \\ \dfrac{(k-c_{n+1})^2}{(c_{n+1}-a_{n+1})(c_{n+1}-b_{n+1})} & b_{n+1} < k \le c_{n+1} \\ 0 & k > c_{n+1} \end{cases} \tag{3}$$

$\mu^{'}(k) = \mu_{thin}(k)$ for $n = 1$ and $\mu^{'}(k) = \mu_{med}(k)$ for $n = 2$

$$\mu_{thick}(k) = \begin{cases} 0 & k \le a_3 \\ \dfrac{(k-a_3)^2}{(c_3-a_3)(b_3-a_3)} & a_3 < k \le b_3 \\ 1 - \dfrac{(k-c_3)^2}{(c_3-a_3)(c_3-b_3)} & b_3 < k \le c_3 \\ 1 & k > c_3 \end{cases} \tag{4}$$

where $m < a_1 \le b_1 \le c_1 \le a_2 \le b_2 \le c_2 \le a_3 \le b_3 \le c_3 < q$.

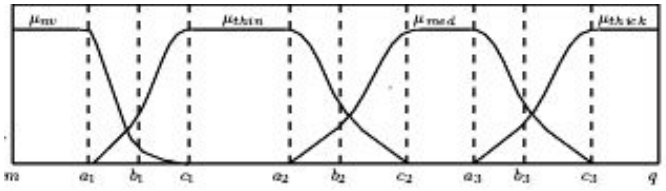

Fig. 2: Membership function for 4-level thresholding

The fuzzy entropy function for the non-vessel class is given by:

$$H_{nv} = -\sum_{k=m}^{q} \frac{p_k * \mu_{nv}(k)}{p_{nv}} * ln\left(\frac{p_k * \mu_{nv}(k)}{p_{nv}}\right) \tag{5}$$

The fuzzy entropy functions for the remaining classes can also be expressed in the similar ways. The total fuzzy entropy function is expressed as:

$$H(a_1, b_1, c_1, a_2, b_2, c_2, a_3, b_3, c_3) = H_{nv} + H_{thin} + H_{med} + H_{thick} \tag{6}$$

The total fuzzy entropy is a function of 9 parameters. In order to extract the retinal vasculatures from the background, a combination of all these 9 parameters is to be determined that maximizes the fuzzy entropy function H. The thresholds that segment the maximum MFR into 4 classes, namely non-vessel, the thin, the medium and the thick vessels are T_1, T_2 and T_3, respectively that can be calculated from the following equation.

$$T_n = \begin{cases} a_n + \sqrt{(c_n - a_n)((b_n - a_n))/2}, & \frac{a_n+c_n}{2} \le b_n \le c_n \\ c_n - \sqrt{(c_n - a_n)(c_n - b_n)/2}, & a_n \le b_n \le \frac{a_n+c_n}{2} \end{cases} \tag{7}$$

for $n = 1, 2, 3$

Step 5: DE for Maximization of Fuzzy Entropy

DE is an efficient and powerful stochastic search technique for solving population based global optimization algorithms. In this work, DE has been implemented to obtain the optimal combination of all the fuzzy parameters and the fitness function to be maximized is considered to be the maximum entropy function given by the following equation:

$$f = \max H(a_1, b_1, c_1, a_2, b_2, c_2, a_3, b_3, c_3) \tag{8}$$

Algorithm 1 describes DE based fuzzy entropy maximization.

Differential Evolution based Fuzzy Entropy Maximization

Input : Randomly initialized population of N individuals $\overrightarrow{P_t} = \{\overrightarrow{X}_1, \overrightarrow{X}_2, \ldots \overrightarrow{X}_N\}$ where the i^{th} chromosome contains a set of 9 optimization parameters and can be expressed as: $\overrightarrow{X}_i(t) = [a_{i,1}, b_{i,1}, c_{i,1}, a_{i,2}, b_{i,2}, c_{i,2}, a_{i,3}, b_{i,3}, c_{i,3}]$, $i = 1, 2, \ldots, N$ uniformly distributed in the range $[m, q]$

Output: Optimal Thresholds that maximize the total fuzzy entropy function

begin
  repeat
    Step 1: Mutation: Generate a mutated vector $\overrightarrow{Y}_i(t)$ corresponding to the target vector $\overrightarrow{X}_i(t)$ for every i.
    for $i = 1$ *to* N **do**
      for $j = 1$ *to* 9 **do**
        $$Y_{i,j}(t) = X_{r_1,j}(t) + F(X_{r_2,j}(t) - X_{r_3,j}(t))$$
        where r_1, r_2, and r_3 are three randomly selected parameter vectors and the scaling factor $F = 0.5$
      end
    end
    Step 2: Crossover: For every target vector $\overrightarrow{X}_i(t)$, create a trial vector $\overrightarrow{Z}_i(t)$ when a randomly generated number between 0 and 1 is less than crossover rate (CR).
    for $i = 1$ *to* N **do**
      for $j = 1$ *to* 9 **do**
        $$\overrightarrow{Z}_{i,j}(t) = \begin{cases} \overrightarrow{Y}_{i,j}(t), & \text{if } rand_j(0,1) < CR(0.9) \\ \overrightarrow{X}_{i,j}(t), & \text{otherwise} \end{cases}$$
      end
    end
    Step 3: Selection: Evaluate the trial vector.
    for $i = 1$ *to* N **do**
      $$\overrightarrow{X}_i(t+1) = \begin{cases} \overrightarrow{Z}_i(t), & \text{if } f(\overrightarrow{Z}_i(t)) \ge f(\overrightarrow{Y}_i(t)) \\ \overrightarrow{X}_i(t), & \text{otherwise} \end{cases}$$
      where $f(.)$ is the function to be maximized.
    end
  until *maximum iteration count is reached*;
  The best chromosome in the population contains the optimal combination of fuzzy parameters. Calculate T_1,T_2,T_3 from equation (7).
end

Once the thresholds T_1, T_2, T_3 are obtained, the image is partitioned into non-vessel, thick, medium and thin vessels which are then logically OR-ed to obtain the entire vascular pattern.

3. SIMULATION RESULTS

This section presents performance of the proposed method tested on DRIVE database [9]. DRIVE database consists of 40 images divided into a training set and a test set, each of them contains 20 images. Both the test and the training set provide manually segmented images. For edge enhancement using curvelet transform, the source code available in [10] is used for curvelet transform. The amplification factor used in the paper to intensify the detailed subbands is 2 which is obtained through simulations over the images in the DRIVE

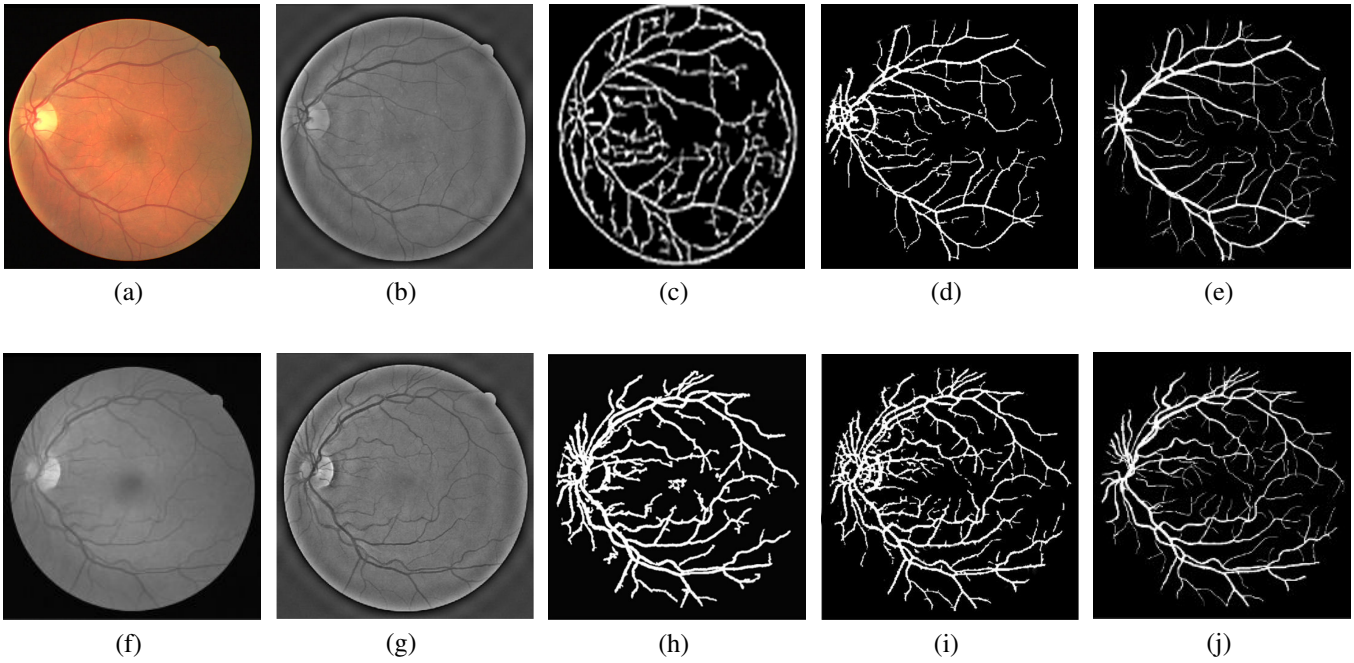

Fig. 3: Simulation Results (a), (f) Original Retinal Image. (b), (g) Edge enhanced image using Curvelet Transform. (c), (h) Vessel Extraction result of [8] and [6], respectively. (d), (i) Extracted vessel map by proposed method. (e), (j) Manually segmented image.

database. Simulation results show that the proposed method performs efficiently with initial population of 100 chromosomes.

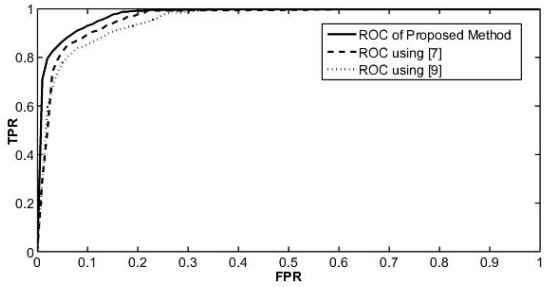

Fig. 4: Comparative study of the ROC curves

The proposed method has been applied to all the 40 images of DRIVE database. However, due to space limitation the extracted vasculatures are shown only for the two images. The results of vessel detection are presented in Fig. 3. The original retinal image and the curvelet based edge enhanced image are shown in the 1^{st} and 2^{nd} column of Fig. 3. The vascular patterns as detected in [8] and [6] are presented in Fig. 3(c) and Fig. 3(h), respectively. The results of the proposed method are depicted in the 3^{rd} column for 50 iterations of DE and the hand labeled ground-truth is presented in the last column of Fig. 3. Comparing 3^{rd} and 4^{th} column, it is observed that some of the tiny vessels which are not detected in Fig. 3(c) and Fig. 3(h), are detected by the proposed method as shown in Fig. 3(d) and Fig. 3(i), respectively.

The metrices used to measure quantitatively the performance of the proposed algorithm include (1) Detection Accuracy (ACC), (2) True Positive Rate (TPR) and (3) False Positive Rate (FPR). The ROC curve has been depicted in Fig. 4. The area under the curve is 0.9523. The values of TPR, FPR, average ACC are shown in Table 1. Numerical values show that both TPR and average ACC of the proposed method are the highest and the value of FPR is the lowest compared to other methods.

Table 1: Comparison of Vessel Extraction Results on Recent Studies

Method	TPR	FPR	Average ACC
Chaudhuri et al [4]	0.6168	0.0259	0.9284
Mendonca et al [2]	0.7344	0.0236	0.9452
Miri et al [10]	0.7352	0.0205	0.9458
Proposed Method	**0.7708**	**0.0183**	**0.9574**

4. CONCLUSIONS AND FUTURE WORKS

An integrated system design for retinal blood vessel extraction is proposed where curvelet transform enhances the curvatures, the contours, the missing and the imprecise edge boundaries followed by intensifying the response using matched filter. The optimal threshold values that maximize the fuzzy entropy function of the maximum MFR classify accurately the different types of vessels and the non-vessels. DE is found efficient to determine the different parameters for the fuzzy function. As observed from the ROC curve, even for the low values of FPR the values of TPR are very high which in turn increases the average ACC of the proposed method. Different types of vessels may now be used for detecting the stage of PDR for further medical purpose.

5. REFERENCES

[1] Keith A. Goatman, Alan D. Fleming, Sam Philip, Graeme J. Williams, John A. Olson, and Peter F. Sharp, "Detection of new vessels on the optic disc using retinal photographs.," *IEEE Transaction on Medical Imaging*, vol. 30, no. 4, pp. 972–979, 2011.

[2] Ana Maria Mendonca and Aurelio C. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction.," *IEEE Transactions on Medical Imaging*, vol. 25, no. 9, pp. 1200–1213, 2006.

[3] Konstantinos K. Delibasis, Aristides I. Kechriniotis, C. Tsonos, and Nicholas Assimakis, "Automatic model-based tracing algorithm for vessel segmentation and diameter estimation," *Comput. Methods Prog. Biomed.*, vol. 100, no. 2, pp. 108–122, Nov. 2010.

[4] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of Blood vessels in Retinal Images Using Two-Dimensional Matched Filters," *IEEE Transactions on Medical Imaging*, vol. 8, no. 3, pp. 263–269, September 1989.

[5] R.J. Winder, P.J. Morrow, I.N. McRitchiea, J.R. Bailie, and P.M. Hart, "Algorithms for digital image processing in diabetic retinopathy," *Computerized Medical Imaging and Graphics*, vol. 33, pp. 608–622, 2009.

[6] Muhammed Gokhan Cinsdikici and Dogan Aydin, "Detection of blood vessels in ophthalmoscope images using mf/ant (matched filter/ant colony) algorithm.," *Computer Methods and Programs in Biomedicine*, vol. 96, no. 2, pp. 85–95, 2009.

[7] Wenbing Tao, Jin-Wen Tian, and Jian Liu, "Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm.," *Pattern Recognition Letters*, vol. 24, no. 16, pp. 3069–3078, 2003.

[8] Mahdad Esmaeili, Hossein Rabbani, Alireza Mehri Dehnavi, and Alireza Dehghani, "Extraction of retinal blood vessels by curvelet transform.," in *Proceedings of International Conference on Image Processing*, November 2009, pp. 3353–3356.

[9] M. Niemeijer, J.J. Staal, B.v. Ginneken, M. Loog, and M.D. Abramoff, "DRIVE: Digital Retinal Images For Vessel Extraction, http://www.isi.uu.nl/Research/Databases/DRIVE," 2004.

[10] Mohammad Saleh Miri and Ali Mahloojifar, "Retinal Image Analysis Using Curvelet Transform and Multistructure Elements Morphology by Reconstruction," *IEEE Transaction on Biomedical Engineering*, vol. 58, no. 5, pp. 1183–1192, May 2011.

[11] http://www. curvelet. org.