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Design and Implementation of Thresholding Algorithm based on MFR for Retinal Fundus Images

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Abstract: *In this paper, the entropy of maximum filter response (MFR) is applied followed by normalization and thresholding for retinal fundus image is used. The performance of our proposed method has been assessed on 23 images representing the publicly available dataset; High-Resolution Fundus (HRF) Image Database.*
Keywords: *Entropy, Fundus Image, Maximum filter response(MFR), Thresholding*

I. Introduction

The Vessel extraction is significant in the survey of [4] digital fundus images since it helps in diagnosing retinal diseases, particularly in evaluating the extremity of the disease in borderline cases. The medical motivation concerning the segmentation of blood vessels of retinal images is to curb the background and accentuate the small vessels so that characteristics such as irregular branching, tortuosity, entropy, neovascularization [5] become more visually prominent. These medical markers assist ophthalmologists in detecting various retinopathies especially diabetic retinopathy (DR), which is a main problem of diabetes. In the view of World Health Organization (WHO), [6] more than 220 million people all over the world have diabetes and deaths because of diabetes are estimated to double between 2005 and 2030. Also, the WHO states that testing for diabetic retinopathy is an expenditure conserving involvement which will help in reducing the difficulty of diabetes (World Health Organization Media Centre, 2015). The main problem faced in vessel extraction of low-resolution images is the effective extraction of the smaller vessels. This is because, during conventional pre-processing methods like smoothing and regular histogram equalization, the shorter vessels get averaged out with the background. This ends in the combining of these vessels with the setting, making it hard to segment them out because of the low variation with the background. Therefore, small vessel enhancement algorithm is applied to the retinal images for better accurate outcomes. However the small vessels are improved, the accuracy of the results would also depend on the effectiveness of the vessel segmentation algorithm. Other structures like the optic disc, fovea centralis, etc. should be removed and only the retinal vessels should be produced, as false detections affect the accuracy of the result. [1] The blood vessels in the fundus images are enhanced by applying Gaussian 2nd order derivative filter successively by varying sigma. In our paper in order to obtain the enhanced blood vessels, the maximum frequency response is chosen from the responses of applied Gaussian filters. As the blood vessels are enhanced very sharply by the Gaussian 2nd order derivative filter, a simple intensity-based thresholding approach is applied to extract the blood vessels.

II. Related Works

Jaeger, Stefan, et al presented their approach using the maximum filter response across all scales.[9] In their method for doing a soft classification the maximum filter response for true red lesions is used. [10] M. Varma et al presented that in Maximum Response (MR) sets, the MR8 filter bank consists of 38 filters but only 8 filters response. The filter bank consists of filters at many positions but their outputs are “collapsed" by recording only the maximum filter response across all orientations. [11] An efficient, mask-size independent algorithm for the maximum filter was proposed by Gil et al. Given the maximum filter response in each pixel, the Non-Maximum Suppression (NMS) reduced to a supplementary differentiation of every pixel value with its maximum neighbor was presented.[12] M. Varma et al compared the performance of these three models proposed by Cula and Dana, Leung and Malik, Schmid and a rotation-invariant model based on the maximum filter response across all positions for every filter type. [13] M. Varma et al used the VZ-MR8 (maximum filter response independent of orientation) descriptor and SVM (Support Vector Machine) with 2 kernel for classification. [14]

III. Proposed Algorithm

3.1 Maximum Filter Response(MFR) by Entropy-based thresholding

In order to segment out blood vessel from retinal image, MFR image is processed by entropy-based thresholding scheme. This takes into account the spatial distribution of gray intensities, is applied as image pixel intensities are not independent of each other. Specifically, a local entropy thresholding technique is described in [2] is implemented, which can well preserve the spatial structures in the binarized/thresholded image. Two images with similar histograms but dissimilar spatial distribution will result in different entropy (also dissimilar threshold values).

The co-occurrence matrix of the image *F* is a $P \times Q$ dimensional matrix $T = [t_{ij}]_{P \times Q}$ that gives an idea of the change of intensities between neighboring pixels, indicating spatial structural information of an image. Depending on the methods in which the gray level *i* pursues gray level *j*, different definitions of co-occurrence matrix are possible. So, we made the co-occurrence matrix asymmetric by allowing the horizontally right and vertically lower transitions.[7] So, t_{ij} is termed as follows:

$$t_{ij} = \sum_{l=1}^{P} \sum_{k=1}^{Q} \delta \tag{1}$$

$$\delta = 1 \quad if \begin{cases} f(l,k) = i \quad and \quad f(l,k+1 = j) \\ \quad or \\ f(l,k) = i \quad and \quad f(l+1,k) = j \end{cases}$$
$$\delta = 0 \qquad otherwise$$

where

$$\delta = 1 \quad if \begin{cases} f(l,k) = i \quad and \quad f(l,k+1 = j) \\ \quad or \\ f(l,k) = i \quad and \quad f(l+1,k) = j \end{cases}$$
$$\delta = 0 \qquad otherwise$$

The probability of co-occurrence p_{ij} of gray levels *i* and *j* can, therefore, be written as

$$p_{ij} = \frac{t_{ij}}{\sum_i \sum_j t_{ij}} \tag{2}$$

If $s, 0 \le s \le L-1,$ is a threshold. Then *s* can partition the co-occurrence matrix into 4 quadrants, into A, B, C and D. We can define the following quantities:

$$P_A = \sum_{i=0}^{s} \sum_{j=0}^{s} p_{ij} \tag{3}$$

$$P_C = \sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} p_{ij} \tag{4}$$

Normalizing the probabilities within each separate quadrant, as the sum of the probabilities of every quadrant equals one, [8] we get the following cell probabilities for different quadrants:

$$P_{ij}^{A} = \frac{p_{ij}}{P_A} = \frac{t_{ij} \Big/ \left(\sum\limits_{i=0}^{L-1} t_{ij} \right)}{\sum\limits_{i=0}^{s} \sum\limits_{j=0}^{s} t_{ij} \Big/ \sum\limits_{i=o}^{L-1} \sum\limits_{j=0}^{L-1} t_{ij}}$$

$$= \frac{t_{ij}}{\sum_{i=0}^{s}\sum_{j=0}^{s} t_{ij}} \quad (5)$$

for $0 \le i \le s, 0 \le j \le s$

Similarly,

$$P_{ij}^{C} = \frac{p_{ij}}{P_C} = \frac{t_{ij}}{\sum_{i=s+1}^{L-1}\sum_{j=s+1}^{L-1} t_{ij}} \quad (6)$$

for $s+1 \le i \le L-1, s+1 \le j \le L-1$

The second order entropy of the object can be defined as

$$H_A^{(2)}(s) = -\frac{1}{2}\sum_{i=0}^{s}\sum_{j=0}^{s} P_{ij}^{A} \log_2 P_{ij}^{A} \quad (7)$$

Likewise, the second-order entropy of the background can be written as

$$H_C^{(2)}(s) = -\frac{1}{2}\sum_{i=s+1}^{L-1}\sum_{j=s+1}^{L-1} P_{ij}^{G} \log_2 P_{ij}^{C} \quad (8)$$

Hence, the total second-order local entropy of the object and the background can be written as

$$H_T^{(2)}(s) = H_A^{(2)}(s) + H_C^{(2)}(s) \quad (9)$$

The gray level corresponding to the maximum of H_T^2 gives the optimal threshold for object-background classification

3.2 Algorithm

Step 1: Select maximum response of Gaussian filter
D = max (*D(x, x), D(x, y), D(y, y)*)
Step 2: *BVE* (D) $\Rightarrow$ Blood vessel extraction
D = Norm (*D*)
Step 3: Apply entropy thresholding to obtain blood vessel extracted image
BV = Enthresh (D)

IV. Experimental Results

The proposed technique is tested using the publicly available dataset High-Resolution Fundus (HRF) Image Database. [3] At first the input image is preprocessed and derivative filters are applied. Then maximum filter response is applied followed by normalization and thresholding.

4.1 Dataset

The public database contains at the present fifteen images of healthy patients, fifteen images of patients with diabetic retinopathy. The proposed method uses fifteen images of healthy patients, eight images of patients with diabetic retinopathy out of 15 images. [3]

4.2 Discussion

The proposed method is used to extract the blood vessels; in our experiments, a set of 23 colour retinal images from the publicly available datasets were used. This gives a good opportunity to test the algorithm on images with different features; normal, abnormal, different sizes. The algorithm is implemented using Matlab. The proposed technique is tested using the publicly available dataset High-Resolution Fundus (HRF) Image Database. The work is extended to implement to calculate the tortuosity of retinal blood vessels.

V. Conclusion

In this paper, a new algorithm for vessel extraction for thresholding based on the entropy of maximum filter response is proposed. This is achieved by means of preprocessing followed by derivative filters. The proposed algorithm is tested using the publicly available database. This work can be extended to calculate the tortuosity of retinal vessels combining with another method.

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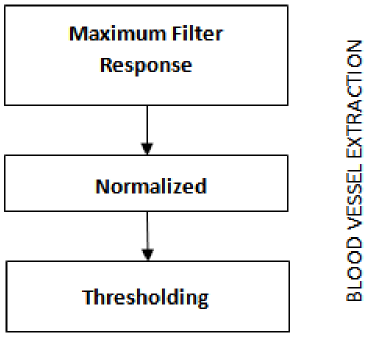

Fig 1. Flow chart of the proposed algorithm

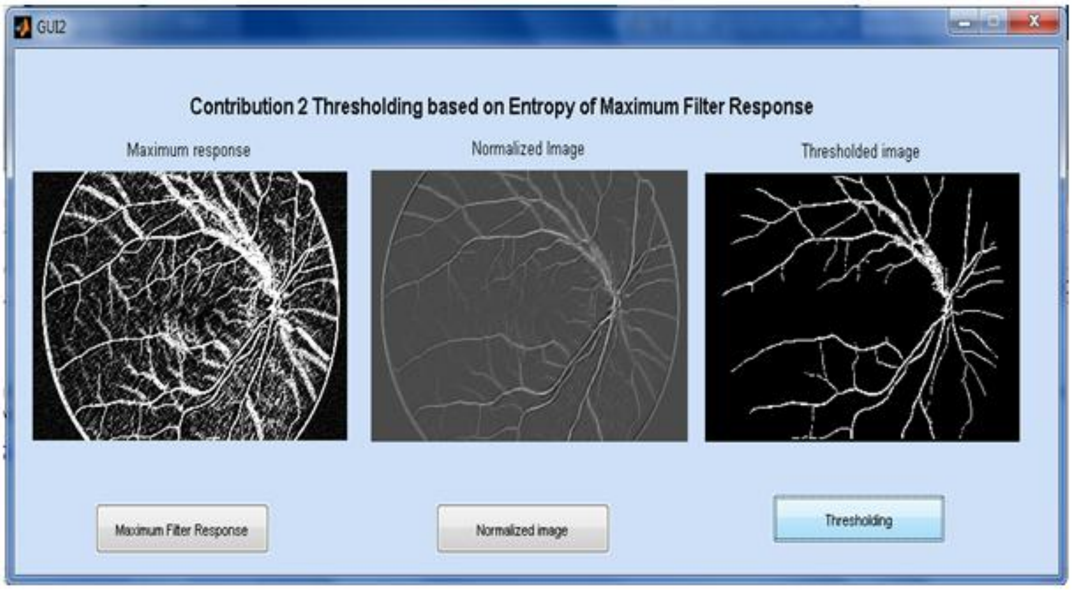

Fig 2. GUI for Thresholding based on Entropy of Maximum Filter Response