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The Diagnosis of Diabetic Retinopathy Disease via Vascular Structure Graph Matching

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Abstract. Diabetic retinopathy is a chronic retinal disorder that affects nearly all patients with diabetes mellitus, albeit with different severity. In this paper a new method based on graph matching is offered. Mentioned method has three main phases which in the first phase, entered image is preprocessed in order to become an image with uniform background and appropriate contrast. Then image is segmented by matched filter with Gaussian-Hermite kernel and retinal vessels will be extracted. In the second phase vascular structure graph is created with fractionating and in the last phase neural network is used for diagnosing normal images and images with signs of diabetic retinopathy. Images that are used for recommended method are derived from the ImageRet database. This offered method has appropriate accuracy for distinguishing healthy and unhealthy images.

Keywords: Diabetic Retinopathy, Matched Filter, Graph Matching, Neural Network, Retinal Images.

1. INTRODUCTION

Diabetic retinopathy is a chronic retinal disorder that affects nearly all patients with diabetes mellitus, albeit with different severity. Diabetic retinopathy is characterized by gradually progressive alterations in the retinal microvasculature and is the main factor of low vision and blindness aged 20-60 years. If diabetes disease lasts longer, Diabetic Retinopathy's possibility increases. In 80 percent of people who suffer diabetes for at least 15 years retinal vessels injury is observed [1]. Diabetic Retinopathy's symptoms include: 1-Microaneurysm (little Protrusions in capillaries). 2-Cotton Wool spots: this spots are swelled ends of axons in nerve fiber layer of retina in spaces that blood circulation is disturbed.3- Turgid and meandrous vessels. 4- Interstitial anomaly of small vessels. 5- Bleeding in different layers of retina [2].

The first sign of developing changes in vessel's walls in Diabetic Retinopathy are microaneurysms which appear as red spots on retina's surface. Microaneurysms can't develop blindness on their own, but not paying attention to disease and its development leads to developing new vessels and also other symptoms and finally leads to visual impairment. Detailed examination of the retina to detect diseases of the organs needs a kind of accurate imaging from its constitutive layers. Early diagnosis of this disease is necessary for success in treatment [3]. Retinal images because of imaging process and convex form of retina have non-uniform lighting and consist of various types of contrast and lighting intensity. This problem seriously affects the detection process.

The first Diabetic Retinopathy early symptom's detection algorithm has been offered by Lay in 1983 .In this algorithm Opening morphological operator with linear structural element has been used. Elimination of microaneurysms and preservation of spots relating to retinal vessels are opening operation's results. Final consequence is resulted from subtraction of opening operation's outcomes from primary image [4].

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Spencer et al offered morphologic conversion method for determining microaneurysms in 1983. In this procedure after gaining preliminary results, they are improved by a classification method [5].

Generally, review on this areas studies shows that most of present methods have morphological base. While in this paper a new method based on graph matching structure is proposed for diabetic retinopathy.

2. MATERIALS AND METHODS

The ImageRet database was made publicly available in 2008 and is subdivided into two sub-databases, DIARETDB0 and DIARETDB1 [6]. DIARETDB0 contains 130 retinal images of which 20 are normal and 110 contain various symptoms of diabetic retinopathy. DIARETDB1 contains 89 images out of which 5 images are of a healthy retina while the other 84 have at least some signs of mild proliferative diabetic retinopathy. The images are acquired with a 50◦ FOV using a fundus camera with unknown settings at a size of 1500 × 1152 pixels in PNG format. Recommended algorithm is implemented and examined in MATLAB software.

In recommended method, image is segmented by matched filter with Gaussian-Hermite Kernel and then is transferred to graph by fractionating and finally neural network is used for separating healthy image from unhealthy one.

3. RETINAL BLOOD VESSELS EXTRACTION USING GAUSSIAN-HERMITE MODEL

We can separate blood vessels from background by image processing technics because retina vessels have distinct features. For extracting blood vessels of retina from colorful images, at first preprocessing phase is applied on image, in order to make it ready for entering to next parts. Retina's images are colorful, for processing these images we try to converse them to gray image with the best contrast. For detection of retina's vessels, various approaches and methods have been introduced so far, that each has special positive and negative features [7, 8] references are assigned for reviewing vessels detection's methods. Retinal images segmentation methods are classified in seven main categories, including: 1) pattern recognition techniques, 2) multi-scale approaches, 3) vessel tracking/tracing, 4) matched filtering, 5) model based approaches, 6) mathematical morphology and 7) parallel / hardware based approaches.

On the whole, vessels detection algorithms have some difficulties for diagnosis, such as: 1) presence of noise, 2) low contrast between vessels and image's background, 3) variability of width, lighting intensity and vessels form. This paper presents a vascular representation and segmentation algorithm based on a multi-resolution Gaussian-Hermite model (MGHM). A 2D Gaussian-Hermite polynomial intensity model is developed which models blood vessel profiles in a quad-tree structure over a range of spatial resolutions. Using this method leads to powerful analysis, decrease computational complexity and respond to thin vessels and low contrast very well.

Blood vessels in retinal images usually have poor local contrast so that the matched filter is designed to detect and enhance the local piecewise vessel segments through image convolution. To approximate the vessel profile, Gaussian function is commonly adopted as the kernel of matched filter. However, in some cases, the intensity profile of some wide vessel segments is not Gaussian due to vessel central light reflection effect. Hence, we use a Gaussian-Hermite mixture model described in [9] to approximate local vessel segment structures. The 1-D second-order Gaussian-Hermite kernel is defined by equation (1):

$$H(x) = \left(1 + a\left(x^2 - 1\right)\right)\frac{1}{2\pi\sigma^2}e^{\left(-x^2/2\sigma^2\right)} \tag{1}$$

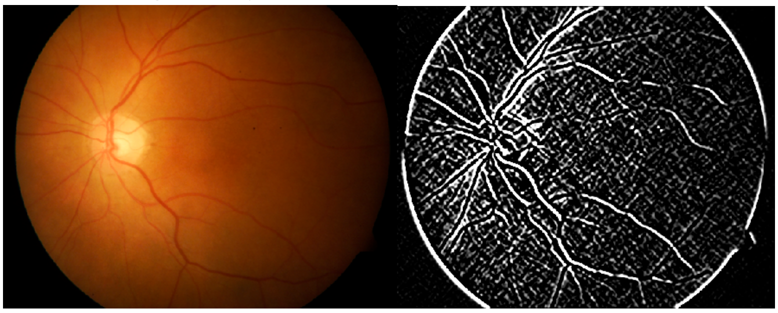
Where a is a weight parameter, that when $a = 0$, the kernel is Gaussian. In order to detect a vessel oriented in any directions, a set rotated kernel is applied to a fundus image. Because of symmetry, only 0◦ ∼ 180◦ possible directions are required for computation. At each orientation, the two-dimensional kernel can be represented as two one-dimensional kernels applied in succession according to Cartesian separability rule. Let $I(u,v)$ be the image intensity at position (u,v), a matched-filter response (MFR) of the input image at orientation θ is defined by equation (2):

$$MFR(u,v,\theta) = -\iint_{-\infty}^{\infty} H_{vv}(v-x)H(u-y)I(x,y,\theta)\,dx\,dy, \tag{2}$$

Where $H(x)$ is Gaussian-Hermite kernel in normal direction of θ, $Hvv(x)$ is second-order derivative of the Gaussian- Hermite kernel along the direction of θ. To make the implementation easier, the image coordinate is rotated at each orientation instead of rotating convolution kernels. Finally, the matched filer is implemented by maximizing the responses over all orientations at each pixel, which can be expressed by equation (3):

$$M(u,v) = \max_\theta\{MFR(u,v,\theta)\}, \qquad 0^\circ \le \theta < 180^\circ. \tag{3}$$

After the main vascular structures were detected, we used a threshold probing technique to distinguish between enhanced vessels and the image background. Result gained from segmentation is shown in Figure 1 by matched filer.



(a) **(b)**

Figure 1.(a) Sample of digital fundus retinal image, (b) Image segmentation by matched filter.

4. FRACTIONIZING IMAGES

Fractioning is one of the main phases in processing image and is a process that divide image to separate parts in a way that each part contains connected and adjacent pixels. The goal of fractionizing is decomposing image into meaningful and easy parts. Other applications of fractionizing images are emplacement of tumors and other damages, measuring tissue's volume and disease detection, face recognition, fingerprint recognition and computer vision. Many methods for fractionizing image have been performed so far amongst we can point to statistical methods, phasic clustering method, optimization method and graph based methods [10].

Statistical methods are very efficient but expensive. Phasic clustering methods have good efficacy but aren't very efficient for images with noise. In optimization methods, fractionizing image is performed with evolutionary algorithms such as genetics, optimizing particle mass, ant colony, prohibited search and…algorithms. Each of these methods has its advantages and disadvantages.

Graph based methods are used for fractionizing image effectively and are so efficient. In this method, image becomes a graph without direction. Image's pixels form graph's nodes and two adjacent nodes are connected with edges. Then graph divides to several parts according to special criterion [11]. Among these criterions, we can point to different methods of graph cut such as minimum cut, normal cut, isometric cut and also optimizing methods such as genetic, ant colony, prohibited search and gradual refrigeration algorithms.

4.1. Graph Partitioning Problem

Graph partitioning is grouping graph nodes into two or several parts according to special criterions such as node's location, node's value (node's density in fractionizing image) or nodes connections. Graph cut technics are used for graph partitioning. The graph partitioning problem is as follows.

Given a graph $G = (N, E)$ (where N is a set of weighted nodes and E is a set of weighted edges) and a positive integer p, find p subsets $N_1, N_2 \ldots\ldots N_p$ of N such that 1) $\bigcup_{i=1}^{p} N_i = N$ and $N_i \cap N_j = \emptyset$ for $i \neq j$, 2) $w(i) \approx \frac{w}{p}, i = 1,2,3, \ldots\ldots, p$,where $w(i)$ and w are the sums of node weights N_i and N , respectively, 3) the cut size, i.e., the sum of weights of edge crossing between subsets is minimized. Any set $\{N_i \subseteq N : 1 \leq i \leq p\}$ is called a $P\_way\ partition$ of N if it satisfies condition (1). (Each N_i is then a part of the partition.) Graph bisecting is a 2-way partitioning. A partition that satisfies condition (2) is a balanced partition [12].

According to above definitions, cost function is defined by equation (4):

$$min \sum_{i,j=1}^{n} E(i,j) + E(j,i) \qquad (4)$$

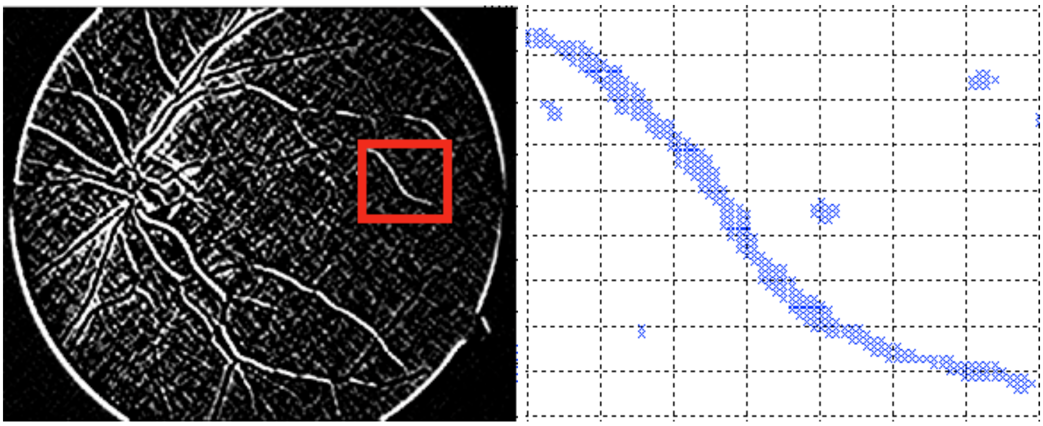
This function express edges that are between two sets of cut are summed together.

4.2. Image fractioning Based on the graph

Graph based fractionation methods, shows the issue in the form of $G = (N, E)$ graph as each graph's node is representative of one pixel in image and each edge connects adjacent pixels.

Based on the graph formulation, there are two groups of methods in the image segmentation problem: 1) region-based methods where each node represents a connected set of pixels, 2) pixel-based methods where each node corresponds to each pixel of the image [13]. In general, region-based methods, like watersheds, produce an over-segmentation of the input image. The over-segmentation image is modelled by means of the RAG, where adjacent regions are merged in order to reduce the number of regions until a meaningful segmentation is obtained. In general, in the merging process, these methods take into account only local information. For more complex images, where there are occlusions or discontinuous objects, this approach does not always yield to an adequate segmentation result.

Pixel-based methods work at very low level of detail, grouping pixels based on a predefined similarity criterion. These methods construct an undirected weighted graph, taking each pixel as a node and connecting each pair of pixels with a weighted edge. This reflects the likelihood that these two pixels belong to the same object. In pixel-based methods, segmentation criteria are based on global similarity measures. After that retina images are segmented by matched filter, images are conversed to graph by fractioning and data relating to each image's graph that contains nodes and edges, are stored in matrix. Graph structure of some part of retina vessels is shown in Figure 2.



(a) (b)

Figure 2. (a) Image resulted from segmenting, (b) Graph of specified part of vessel.

5. DİSTİNGUİSHİNG SOUND and UNSOUND İMAGES BY ACKPROPAGATİON NEURAL NETWORK

Artificial neural network is a processing system of data that is made according to human's brain. In artificial neural network small processors that connect with each other for solving problems, process data. Neural networks with their significant ability in results inference from complex data can be used in extracting patterns and identifying different orientations that are hard to identify for human and computer.

In this article, backpropagation neural networks are used for recognizing healthy and unhealthy images. Backpropagation algorithm performs based on maximum gradient reduction. In this algorithm, square of errors is efficiency indicator. The first phase before designing and training network is creating appropriate input and output network data. In vascular structure graph matrix, several sound images are used for training. In network testing part, in the condition that an image is similar to normal patterns, neural network's output will be 1 otherwise output will be -1 which reflects the structure of the retinal vessels are unhealthy [14].

6. CONCLUSİON

In this paper digital images of the human retina are processed. Then with considering researches in this context, an algorithm for diagnosing Diabetic Retinopathy is offered by graph matching. At first, preprocessing is performed on images for correcting retinal images lighting and contrast. For optimized extraction of blood vessels from retinal images, matched filter with Gaussian-Hermit Kernel is applied. The two dimensional Gaussian-Hermite model provides better responses to thin and low-contrast vessels and reduces the computational complexity. Then images are conversed to graph by fractioning. Studying sound images graph shows that normal images have similar graph structure. Finally, backpropagation neural network is used for recognizing healthy images from unhealthy ones. Results show that recommended method has proper functioning in separation of healthy and unhealthy images.

Our future work will be focusing on the relationship of retinal vascular geometry (RVG) changes with increased severity of diabetic retinopathy. Moreover, changes in vascular structure can act as a new sign in recognizing networks that are in danger of proliferative diabetic retinopathy.

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