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Segmentation Based Vessel Extraction of Retina

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Abstract—: Advancements in image processing and computing has lead to its use in various applications in medical imaging. In the field of ophthalmology, retinal analysis is used for medical diagnosis and detection of the diseases. Various diseases such as diabetic retinopathy, age-related macular degeneration, muscular dystrophy can be easily diagnosed using automated diagnostic systems, thus providing resource savings. The present paper reviews image segmentation based techniques for retinal analysis which is used to provide retinal microvasculature non-invasively. A brief comparison is between pixel-based and tracking based techniques is also provided.

Keywords— Retina, vessel extraction, segmentation, retinal microvasculature, vessel tracking.

I. INTRODUCTION

Retina is a tissue that acts like a screen in human eye for image formation. It contains the vessel structure, cells for transforming the incoming photoreceptors signals into analog signals that can be send down the optic nerve to the brain for processing. It is a part of brain as it develops from an embryonic forebrain [2]. First known image of human retina as drawn by Van Trigt [6] is shown in Figure 1. As its function requires seeing the outside world, therefore, the ocular structure needs to be transparent and reach of light rays to the retinal structure must be possible. Because of its architecture dictated by its function, both diseases of the eye as well as diseases that affect the circulation and the brain can manifest themselves in the retina.

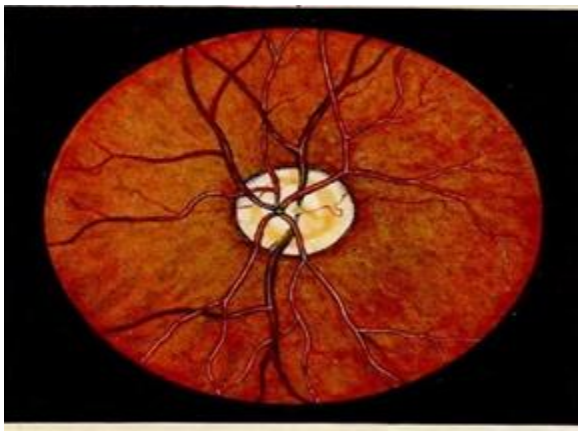

Fig. 1. First known image of human retina as drawn by Van Trigt [6].

These include ocular diseases, such as macular degeneration and glaucoma, the first and third most important causes of blindness in the developed world. A number of systemic diseases also affect the retina. Complications of such systemic diseases include diabetic retinopathy from diabetes, the second most common cause of blindness in the developed world, hypertensive retinopathy from cardiovascular disease, and multiple sclerosis. Thus, on the one hand, the retina is vulnerable to organ-specific and systemic diseases, while on the other hand, imaging the retina allows diseases of the eye proper, as well as complications of diabetes, hypertension and other cardiovascular diseases, to be detected, diagnosed and managed. The retinal vessel structure is thus a new way to diagnose diseases prevalent in the eye. As blood flow increases and decreases in the vessel structure thus causes prevalent damage to the eye structure which can be detected by diagnosing the retinal

A. Anatomical Structure of Eye

For a better review of the retinal segmentation methods, the anatomy of eye is essential to be understood. This is shown in Figure 2. It consists of the normally visible part transparent cornea, the white sclera. Next comes the colored (blue, brown, black or mixture) iris and an opening in the iris, which is black in color known as pupil. The ray of light partially focused by the cornea passes through the anterior chamber, lens, and pupil further focusing the image and then reaches

retina through the vitreous humor. The retina itself is supported by its retinal pigment epithelium, which is normally opaque, the choroid and the sclera. The blood supply of the retina is primarily (65%) through the choroid and secondarily (35%) through the retinal vasculature which lies on top of the retina. It is useful to divide the retina and choroid into the following layers:

1) Internal limiting membrane;
2) Nerve fiber layer (the axons of the ganglion cells, that transmit the visual signal to the lateral geniculation nucleus and thence the visual cortex);
3) Ganglion cell layer (the cell bodies of the ganglion cells);
4) Inner plexiform layer (the axons of the bipolar cells);
5) Inner nuclear layer (the cell bodies of the bipolar and horizontal cells);
6) Outer plexiform layer (the dendrites of the horizontal cells and the inner segments of the rod and cone photoreceptor cells);
7) Outer nuclear layer (cell bodies outer segments of the photoreceptor cells);
8) External limiting membrane;
9) Pigment epithelium;
10) Bruch's membrane;
11) Capillary choroid (capillaries of the choroid);
12) Choroid plexus.

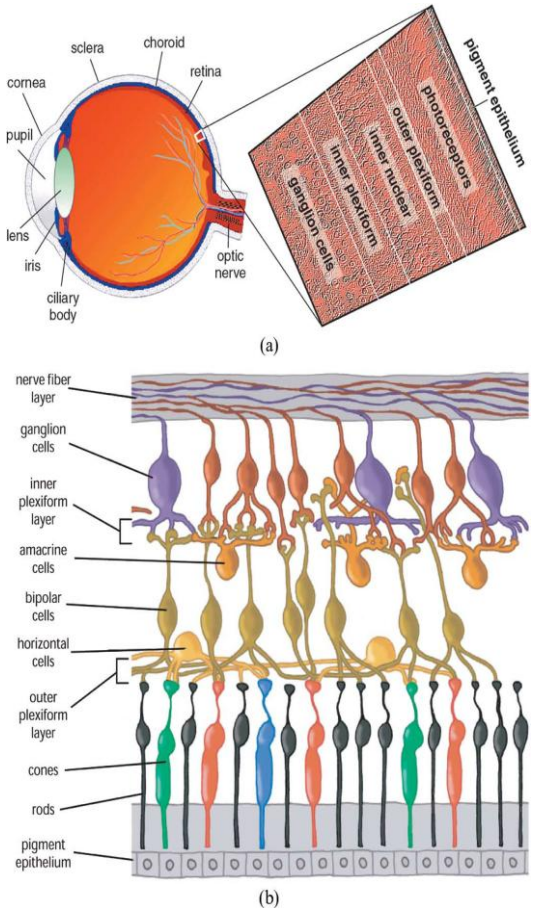

Fig.2. Anatomy of Eye a) Layers of Retina, and b) Layers of Choroid.

B. Retinal Manifestations of Eye and Systemic Disease

Many important diseases manifest themselves in the retina and originate either in the eye, brain or cardiovascular system. A brief overview of the most prevalent diseases that can be studied via eye imaging and image analysis follows:

1) *Diabetes:* Diabetes mellitus, according to the current definition from the World Health Organization, is typically diagnosed if a patient has fasting plasma glucose over 7.0 mmol/L[1]. Hyperglycemia, the presence of elevated blood glucose, is known to damage small and large blood vessels, as well as nerve cells, and thereby damages the kidneys, heart, brain and eyes, and results in a retinal complication of diabetes called *diabetic retinopathy*.
2) *Diabetic Retinopathy:* Diabetic retinopathy (DR) is a complication of diabetes mellitus and is second most common cause of blindness and visual loss in the U.S. There is abundant evidence that blindness and visual loss in these patients can be prevented through annual screening and early diagnosis[1]. In the eye, hyperglycemia damages the retinal vessel walls, which can lead to:
    a) *Ischemia*, resulting in the growth of new blood vessels, which may subsequently bleed and/or cause retinal detachment, a condition called proliferative diabetic retinopathy;

b) *Breakdown of the blood-retinal barrier*, leading to fluid leakage, diabetic macular edema (DME) and damage to photoreceptors.

II. LITERATURE SURVEY

Retinal microvasculature is affected by structural and functional changes, which are caused by diseases affecting the vasculature. It is the only place where the blood vessel structure can be accessed non-invasively in vivo, through the techniques of retinal imaging. Changes in retinal vasculature, such as haemorrhages, angiogenesis, increases in vessel tortuosity, blockages and arteriolar-venular diameter ratios are important indicators of, diabetic retinopathy, retinopathy of prematurity and cardiovascular risk. The detection of landmark features of fundus such as the optic disc, fovea and blood vessels can be done by automated diagnostics or manual ways.

Retinal images are influenced by all the factors that affect the body vasculature in general. Moreover the eye is the very unique region of the human body, where, the vascular condition can be directly observed *in vivo*. Along with the fovea and optic disc, the vascular tree constitutes one of the main features of an ocular fundus image and several of its properties are noticeably affected by worldwide major diseases such as diabetes, hypertension, and arteriosclerosis. The methods used for identifying vessels in two-dimensional (2-D) images are generally based on local image features, taking into account the specific properties of the vascular segments. Two main approaches are normally considered for identification of general vascular segments, associated with two different strategies for classifying each pixel as belonging to a vessel or not. These two categories are also found in retinal vasculature segmentation applications, where the algorithms for detecting blood vessels are generally grouped as *pixel processing- based* methods and *tracking* methods.

A. Pixel Processing-Based Methods[2]

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[1]. The kernel is rotated into many different orientations (two or 12) to fit into vessels of different configuration. The images are then thresholded (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 a central line 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.

B. Tracking Methods[2]

Tracking methods start by locating, manually or automatically, the vessel points used for tracing the vasculature, by measuring some local image properties. These methods, that only evaluate the pixels close to the initial positions, are also mentioned as exploratory algorithms. The algorithms are normally implemented as a single-pass operation, where the extraction of image features and the recognition of the vessel structure are simultaneously executed. Most of the methods reported in the literature use Gaussian functions to characterize the vessel profile. A technique for vessel segmentation include ‘‘Vessel-Tracking”, where by vessel centre locations are automatically sought over each cross-section of a vessel along the Vessels longitudinal axis, having been given a starting and end point [1]. They tend to work on single retinal vessels and require starting and ending points to be identified by the user. The selection of vascular points is normally accomplished by matched filters. In addition, vessel -tracking techniques may be confused by vessel crossings and bifurcations. However, vessel tracking can provide very accurate measurements of vessel widths and tortuosity. The present paper concentrates on the comparison between pixel processing based techniques and the vessel tracking methods by taking two implemented algorithms and making their comparison.

III. SEGMENTATION BASED ALGORITHMS

The comparison is made between the two algorithms based on the degree of automation and the area spanned both in the pixel processing based methods as well as the vessel tracking methods. The algorithms compared are automatic segmentation algorithm [5] and 2-D vessel tracking [4].

A. Automatic Segmentation Algorithm

The algorithm is based on the pixel processing method, implementing region growing using seed pixels as shown in Figure 3. Different stages of this segmentation algorithm are described below:

1. Image Enhancement: Spatial or Frequency Domain techniques form the basis for image enhancement. The spatial domain refers to the aggregate of pixels composing an image. Convolution theorem forms the basis for frequency domain

techniques whereas spatial domain techniques operate directly on the pixels. In the spatial domain, images are enhanced by applying transformation functions on the gray levels of the pixels directly.

Here, power-law transformation is used at the contrast enhancement step since the traditional histogram equalization (HE) methods suffer from many drawbacks such as not having a mechanism that adjust the degree of enhancement and causing undesired visual artifacts. Power-law transformation is useful for such a contrast manipulation and is defined as follows:

$$S = c\,F(i, j)$$

Where c and γ are positive constants. A family of possible transformation curves can be obtained just by varying the γ. Power-law curves with fractional values of γ map a narrow of dark input values into a wider range of output values, with the opposite being true of higher value of input level.

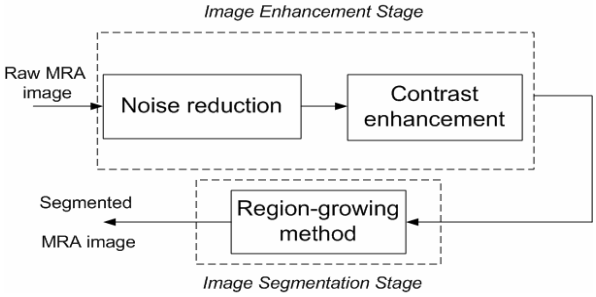

Fig.3. Segmentation based Algorithm [5]

2. Image Segmentation: Region-growing method is used at the image segmentation stage using homogeneity criterion with respect to gray level information to extract vessels structures[5]. An algorithm for region growing by pixel aggregation based on the similarity of a local property (which is the intensity level) is as follows:

a) Start with a seed pixel (or a set of seed pixels).
b) Append to each pixel in the region those of its 8-connected neighbors that have properties (intensity level) that are similar to those of the seed.
c) Stop when the region cannot be grown any further.

The result of the algorithm above depends on the procedure used to select the seed pixels and the measures of similarity or inclusion criteria used.

Selection of Seed Pixels: The algorithm selects the seed pixels based on the median or the mean value of the image. Vascular structure is relatively brighter than the other areas for the TOF-MRA images. Every pixel with a value greater than the median gray level of the image is identified as a potential seed pixel for the next steps. This selection scheme is easy and effective in most cases. A region of interest (ROI) is determined by automatically selecting two points on the MRA image. This helps to restrict and constrain the region-growing to within the ROI. A seed point for the region growing algorithm is automatically defined at the center of the ROI. In parallel, the average pixel intensity in the neighboring region is calculated and is defined as the initial feature metric. Consequently, a search is conducted to determine the pixel which has the least intensity difference from the initial average intensity. The determined pixel is then added to the region. Thus, this process provides the automation of covering the wider region of the retina and providing the eye vessel structure.

B. 2-D Vessel Tracking Algorithm

This method is based on vessel tracking using 2-D physical model. The vessel width and orientation is determined by choosing an initial point and then taking further steps in the vessel orientation. The procedure is repeated until the complete vessel is traced out in the local region. The methods based on edge detection, convolution operators based on vessel shapes can suffer from insufficient number of edge pixels. These have to be applied on various orientations thus increasing the process time. It can be overcome by using a physical blood vessel model with an optimization procedure such as non-linear least square fit method. By using a two-dimensional local region about the current point a very accurate estimate both of vessel width and vessel orientation can be made[4].The physical model for blood vessel can be derived by assuming that vessels attenuates the red free-light as it passes through the blood column. Attenuation is according to Bouguer's Law, and the exit beam intensity is given by,

$$I(x) = I_o\, e^{-\int \alpha(x,z)\,dz}$$

where α(x, z) is the linear attenuation coefficient, x is the dimension in the plane of the retina across the vessel and z is depth into the retina[4].Taking α as constant throughout the vessel, and the vessel profile as symmetric and circular, then to second order the received light is,

$$I(x) = I_o\,(1 - ae^{-(x-x_o)^2/2\sigma^2})$$

Where x_o is the centre of the vessel, σ defines the width of the vessel, and a is a constant giving the relative amount of light absorbed by the vessel. It represents the basic idea over which this 2-D model is based. The 2-D model extends the vessel in the orientation orthogonal to its cross section. Vessel extensions are assumed to be Linear and uniform. The cross section is assumed to be same across all points at the local level. A small region is cut out around the local point y using 2-D non-linear least square fit method. Given a point (x,y), an estimation of width σ and orientation θ, accurate measurement is enabled by the small region. The current point's measured width and orientation in 2-D is implemented in measuring next step width and orientation. The vessel is traced by incrementing in each step this way. At each step a new 2-D fit is made to the model. The generalization of the model requires that co-ordinates (x, y) and orientation θ of vessel with respect to the x-axis. New co-ordinates (u, v) are constructed with u pointing in the vessel direction and v orthogonal to the vessel, then

$$u = x \sin\theta - y \cos\theta$$
$$v = x \cos\theta + y \sin\theta$$

Using single Gaussian profile model,

$$I(v) = A - Be^{-(v-v0)2/2\sigma 2}$$

Here, A is the background intensity and B is the contrast of the vessel with respect to the background and v0 enables the vessel centre to be shifted in the v-direction. It is not always the case that a vessel is linear as it can be tortuous and bend in the localized region. The tortuosity can be accounted y adding a quadratic coefficient to u which describes the curvature.

$$u = x \sin\theta - y \cos\theta + \acute{\eta} v^2$$
$$v = x \cos\theta - y \sin\theta$$

Where ή describes the curvature of the vessel. If = 0 then there is no curvature of the vessel. If $|\acute{\eta}| > 0$ then the vessel function will bend in the direction of u about the origin. In figure 1 is shown the function for $\acute{\eta} = 0$ and $\acute{\eta} > 0$. A negative ή causes a curvature in the opposite direction. We use the nlinfit routine of MATLAB to effect a non-linear least-squares fit of the model to the underlying image data within the local region. It is an implementation of the Levenberg-Marquardt algorithm and only it estimates the local gradient of the model by numerical differentiation requires specification of the model itself, as it estimates the local gradient of the model by numerical differentiation. The pixels 2ceil(2σ) + 1 pixels along the u axis, and 2 ceil(3 2σ) + 1 pixels along the v-axis defines the local region for the fitting. The region must be in orientation with the vessel to give the reasonable estimation of the vessel width.

IV. Conclusion

Present paper reviews segmentation based algorithms for vessel extraction of retina. The comparison of the two algorithms shows that the pixel based processing techniques are not only limited to a local region of the retina but spans the whole area of retina producing the vessel structure. Whereas vessel tracking is an efficient but costly technique as it moves from vessel to vessel, tracking its width and the adjoining pixels. However, it is limited only to the local area. Thus this review paper believes pixel processing based methods to be more efficient and automation oriented, producing the vessel structure in a time oriented manner and are extremely useful in the large screening programs. In future, performance of these segmentation based algorithms can be improved based on performance evaluation parameters.

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