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Retinal vessel extraction by means of motion contrast, matched filter and combined corner-edge detector

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ABSTRACT

The microvasculature network of retina plays an important role in understanding of the retinal function and diagnosis of many diseases. Although it is possible to noninvasively acquire diffraction-limited resolution retinal images at microscopic cellular level, noises and other structures still make it difficult for diagnosis. In this paper, a new vessel extraction method is introduced. First, we use motion contrast method to trace the motion of the blood components and get the main vessel contour. Second, an improved matched filter method is applied to extract the vessel contour while the single-side edges are eliminated. Then, the combined corner/edge detector is adopted to eliminate the elongated fragments caused by the motion artifacts. Finally, we use mathematical morphology method to dilate the edges of vessels acquired in last step and obtain the exact contour of the vessels. The contrast of the vessels is significantly enhanced and the noises as well as other structures are effectively eliminated.

1. Introduction

The retina is a complex and multilayer structure, which can be noninvasively observed in vivo. The microscopic imaging of retina provides an important approach to early diagnosis of many sight-threatening retinal diseases, age-related macular degeneration as well as systemic diseases (diabetes, hypertension et al.) [1,2]. However, ocular aberrations limit the resolution of the retinal images. To overcome this obstacle, a variety of technologies were introduced into the retinal imaging systems (adaptive optics [3], optical coherence tomography [4], scanning laser ophthalmoscope [5], and so on). These technologies made it feasible to noninvasively acquire diffraction-limited resolution retinal images at microscopic cellular level.

Above all of the retinal structure, the microvasculature network plays a vital role in understanding of the retinal function and pathological changes because the microvasculature is the most predominant and stable structures appearing in the images. Since the huge quantity of images precludes strictly manual analysis while the noise and other structures out of focus will mislead the diagnosis, automated vessel extraction is necessary for retinal image processing and analysis [6].

The challenges of vessel extraction in retinal images can be summarized as follows:

- The widths of vessels are fickle, ranging from one pixel to more than 10 pixel.
- Some vessels are low contrast, especially for narrow vessels.
- Noises and other structures, which are out of focus, degenerate the images.
- The central reflex of the wider vessels makes it hard to be distinguished from a pair of side-by-side vessels.

The techniques on retinal vessel extraction may be roughly divided into categories based on: intensity edge methods [7,8], adaptive threshold methods [9,10], matched filter methods [11,12], mathematical morphology methods [13,14], region growing methods [15,16], Hessian-based methods [17,18] and machine learning methods [19,20]. All the methods concentrate on solving the challenges discussed above.

However, these methods discussed above mainly work on high-contrast retinal images (images obtained by fundus camera for example), which are high-contrast. They work badly on low-contrast retinal images (images obtained by AOSLO for example). This paper aims at the extraction of the capillaries, the width of which is less than 10 μm, in low-contrast retinal images (images obtained by AOSLO for example). As far as the authors know, there is no extraction method working on this kind of images. In this paper we introduce a new vessel extraction method, aiming at

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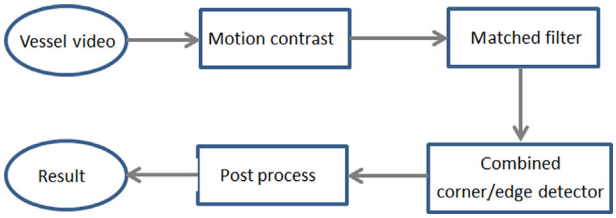

Fig. 1. Flow chart of vessel extraction algorithm by means of motion contrast, matched filter and combined corner/edge detector.

solving the first three challenges discussed above. Because the forth challenge can be overcome by so-called forward scatter method during imaging procedure [21]. The flow chart of the main algorithms is shown in Fig. 1.

The vessel video is acquired with an Adaptive Optics scanning laser ophthalmoscope (AOSLO). The video is 30 fps for 2 s monitoring the same region (275 μm × 286 μm) of the retina. The imaging wavelength is 840 nm, at which waveband some components of blood reflect the light while other components of blood absorb the light. So we can see white flow parcels travelling through vessels. There is still debate in the field as to what the "white parcels" represent. According to Ref. [22], the motion of the parcels will adhere to the vessel walls. Then we can extract the vessel contour by tracing the motion of these white parcels. Because of the error of image registration and motion artifacts, there are many noises in the motion contrast image. Subsequently, we introduce a new multiple-scale matched filter method to distinguish vessels from false edges. To eliminate the effect of motion artifacts, we apply the combined corner/edge detector to the vessel image. Because the combined corner/edge detector has different responses to corners and edges, a local adaptive threshold is applied to acquire the edges which stand for the vessels. Finally, we smooth the vessels in the image through a series of post procedures.

This paper is organized as follows: In Section 2, we discuss the techniques and methods in detail. Then, the experimental condition and result are shown in Section 3. At last, we conclude this paper in Section 4.

2. Description of the methods

2.1. Motion contrast method

The blood mainly contains three components: plasma, erythrocytes and leukocytes. The light absorptions of these components are different at the imaging wavelength. So some components in the retinal image are white parcels while the other components of vessels are dark background, as shown in Fig. 2.

The white parcels travel through the vessels as marked in Fig. 2. Even if the vessels are dark background, the contrast is too low to distinguish the locations of vessels. This is because the photoreceptors are also white dots in the images. The photoreceptors have waveguide properties to return light directly back through the pupil [23]. So the light reflectance of photoreceptors is high as well. The centerline of the vessels is shown in Fig. 2(f).

The low contrast between vessels and background makes it impossible to extract the vessel contour using traditional methods. Since the white parcels travel along the vessel wall, we can make use of the motion of these white parcels to extract the vessel contour. The motion contrast method is similar to the one used in Ref. [24]. The motion contrast method is based on variance map between images, so the images must be cropped into the same size in pixels and the same region of retina. Then, these images pass through a median filter to eliminate the effect of noise. It is also important that the images in the sequence have the same L^2 norm.

$$\|I\|_2 = \sqrt{I(x_1,y_1)^2 + I(x_2,y_2)^2 + \cdots + I(x_n,y_n)^2} \tag{1}$$

here, I is the retinal image, $I(x_1,y_1), I(x_2,y_2), \ldots, I(x_n,y_n)$ are the pixels of I. $\|\|_2$ denotes the L^2 norm.

Once the procedures discussed above have finished, we can go on to trace the motion of the white parcels along the vessels. A mean image $\overline{M}(x,y)$ is calculated from all of the images.

$$\overline{M}(x,y) = \frac{1}{N}\sum_{i=1}^{N} I_i(x,y) \tag{2}$$

where $I_i(x,y)$ represents the intensities of frame i in the video. N is the number of frames in the video. We use $\overline{M}$ as reference image to construct division image $D_i(x,y)$

$$D_i(x,y) = I_i(x,y)/\overline{M}(x,y) \tag{3}$$

In the division image $D_i(x,y)$, pixels at the location of white parcels have large intensities while the pixels at the other parts have small intensities around 1. That is because the other parts of the image are stable when the white parcels are changeable. Then, a threshold, which is slightly larger than 1, is applied to the division images $D_i(x,y)$ to eliminate the stable background. Finally, all the division images $D_i(x,y)$ are synthesized into a single image (motion contrast image).

As shown in Fig. 3(b), the vessel contour is well detected, but we find that there are many white dots in the background, which degenerate the motion contrast image. From the size and distribution of the dots, we consider that it may be caused by two reasons:

(1) The error of image registration: the images of the video are manually registered, and the main error of image registration is the shift from its original location. This kind of error will cause the motion contrast image degenerate on the whole scale of image.
(2) The oscillations of the photoreceptors: the reflectance of some photoreceptors fluctuates within a second or two, which is in accordance with the time for imaging. In some cases, the photoreceptors disappeared and then reappeared [25]. This kind of error will lead to the local variance in some region. The intensity and location of the variance are random.

To eliminate these errors, a combined corner/edge detector is introduced and it will be discussed in Section 2.3.

2.2. Matched filter method

The matched filter method evaluates the correlation between image regions, which potentially contain a blood vessel segment, and the two-dimensional matched-filter masks, which approximate the typical blood vessel segments. If the manually selected blood vessel segments are available, the matched-filter masks can be constructed accordingly [26]. However, there is not any priori knowledge of the vessel images in our case. And our purpose is extracting the vessels automatically. So a reasonable matched-filter mask should be constructed. Since the distribution along the normal direction of the vessels is similar to one-dimensional Gaussian distribution, the matched-filter mask can be derived basing on Gaussian distribution [27].

The tangential distribution of traditional two-dimensional matched-filter mask is constant. That will exaggerate the contribution of the neighbor pixels and result in false vessels, as shown in Fig. 4.

We can see in the figure that: (1) The segments around the corner of vessels exceed the vessel contour and produce false