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Accurate vessel segmentation using maximum entropy incorporating line detection and phase-preserving denoising

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ABSTRACT

The retinal images with lesions, exudates, non-uniformed illuminations and pathological artifacts have intrinsic problems such as the absence of thin vessels and false vessels detection. To solve these problems, we propose a novel algorithm which involves separation of background images to minimize the influence of noise, non-uniformed illuminations and lesions. We develop two different strategies to segment thin and thick blood vessels. Thin blood vessels are identified by taking benefits of local phase-preserving denoising, line detection, local normalization and maximum entropy thresholding. To remove noise and preserve detailed blood vessels information, phase-preserving denoising technique is used. The technology takes an advantage of log-Gabor wavelet responses in the complex domain to preserve the phase information of the image. Thick vessels are extracted and binarized via maximum entropy thresholding. The performance of the proposed algorithm is tested on four popular databases (DRIVE, STARE, CHASE_ DB1, HRF). The results demonstrate that the proposed segmentation process is automatic, accurate and computationally efficient.

1. Introduction

The manifestation of diseases in retinal images is an important investigative indicator of various medical syndromes in relation to eye and body. The ophthalmic diseases such as diabetic retinopathy (Fong et al., 2004; Mohamed et al., 2007), retinal artery occlusion (Beatty and AuEong, 2000) and choroidal neovascularization (The Eye-Disease Case Control Study Group, 1993) could be identified from the different characteristics of blood vessels. To identify these features, blood vessel segmentation is an important and primary step. There are two ways of blood vessel segmentation: manual and automatic (Fraz et al., 2012b). Manual segmentation of blood vessels in an image is complex and exceptionally time consuming that requires training and skill. Hence it is commonly acknowledged by the medical community that automatic segmentation is significantly valuable for accurate and speedy identification of blood vessels. It is vital to have automatic and accurate segmentation algorithm for retinal images to develop a diagnostic system for the treatment of ophthalmic disorders.

Several solutions have already been proposed for segmentation of retinal vessels. Preceding research on the development of methods for blood vessel segmentation can be categorized as supervised (Nekovei and Sun, 1995; Staal et al., 2004) or unsupervised segmentation (Kirbas and Quek, 2004; Yin et al., 2014; You et al., 2006). Segmentation with supervised methods is basically reliant on training sets such as manually segmented gold standard classifications. The information is used to differentiate retina images as vessels or non-vessels. In supervised segmentation methods, a training process such as support vector machines (SVMs) (Bowd et al., 2005; Ricci and Perfetti, 2007), k-nearest neighbors (Osareh and Shadgar, 2010), artificial neural networks (ANN) (Jiang et al., 2010), Gaussian mixture models (GMM) (David et al., 2008; Foroozan et al., 2002) are implemented. In contrast, unsupervised segmentation methods are independent of training datasets, hence are more appropriate to a broader range of imaging modalities. Unsupervised segmentation techniques have been proposed by a wide range of approaches such as texture mapping (Yin et al., 2014), thresholding techniques (Saleh et al., 2010), vessel tracing/tracking (Chutatape et al., 1998; Liu and Sun, 1993), multi-scale approaches (Frangi et al., 1998), model based approaches (Mahadevan et al., 2004; Vermeer et al., 2004), active contour models (Espona et al., 2007), morphological processing (Zana and Klein, 1999; 2001), and matched filter approaches (Chaudhuri et al., 1989). Also, each retinal image shows unique properties with respect to retinal boundaries, optic discs and different diseases (Siddalingaswamy and Gopalakrishna, 2010). Moreover, vessel crossing (Kondermann et al., 2007), bright or dark lesions (Akram and Khan, 2012), low contrast (Sukkaew et al., 2007), uneven illumination

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(Hoover and Goldbaum, 2003), and noise (Passaglia and Troy, 2004) further complicate the segmentation process for an accurate result.

A line detector proposed by Ricci and Perfetti (2007) calculates the average pixel intensity of lines in different orientations and the line with highest average intensity is selected. This technique is effective in dealing with the vessels comprising central light reflex, especially for the long lines. In Ricci and Perfetti (2007), the length of line detector is fixed. Hence, when two vessels are closer, it tends to merge together. Also, it produces false vessels at vessel crossovers. A solution was proposed by Nguyen et al. (2013) using generalized multiscale line detector by varying a length. A shorter line length can be detected efficiently but introduces background noise in the segmented results. Moreover, the same weight assigned for the different line length in Nguyen et al. (2013) produces considerably higher noise and the false vessels near optic disc. It is also observed that the method is ineffective in dealing with the pathological images with bright or dark lesion. Hence the issues observed in the current state of the art that restrict in developing an accurate vessel segmentation algorithm can be summarized as: I) Both non-uniform illumination and background noise of the images are responsible for false vessels. II) Detection of dim and thin vessels in retinal images is a greater challenge. Very few researcher treat thick and thin vessels separately, which results in higher false positives. III) Closer vessels are merged. IV) Most of the blood vessel segmentation algorithms assume that retina is healthy and free of bright and dark lesions (Saffarzadeh et al., 2014). However, the existence of bright or dark lesions can considerably degrade the performance of blood vessel segmentation and even make the result unusable due to detected lesions. To overcome the aforementioned problem, we propose an accurate retinal blood vessel segmentation method. The underlying technique of proposed solution involves summation of filter responses while detection of centerlines in different orientations. Generally, for line detection twelve different orientations are involved (Al-Rawi et al., 2007; Nguyen et al., 2013; Wu et al., 2007). However, it is suggested in Mendonca and Campilho (2006), four different orientations are sufficient to detect the blood vessels with reduced computational complexity. In addition, phase-preserving denoising technique before the centerline detection is highly effective especially for the accurate detection of thin and dim vessels with significantly reduced noisy pixels.

The original RGB retinal images consist of red, green and blue channels. Red channel is the brightest color channel and blue channel displays poor dynamic range. Thus, detailed blood vessels are not represented. In contrast, green channel exhibits highest contrast between blood vessels and background. Hence, green channel image is selected for retinal blood vessels segmentation method (Xu and Luo, 2010). The process begins with a pre-processing step to eliminate non-uniform illumination and noise in fundus image. This step includes background estimation and subtraction. The background estimation is carried out with a morphological opening approach and subtracted from the green channel fundus image. It aims in reduction of drastic variation of illumination and noise existed in the fundus images during pixel classification. Furthermore, optic disc and pathological regions such as bright lesion are treated as background during estimation since these pixels are brighter than the blood vessels and background. Additionally, we contribute a method to accurately segment thin and thick blood vessels from retinal fundus images. Thick blood vessels are clear, distinct and easier to detect while thin vessels are smaller in size, dim and show bad contrast. It is also observed that the gray level intensity and geometrical correlations between thin and thick vessels are different. Hence, thick and thin blood vessels have different characteristics and needs to be segmented using separate approaches. To handle thick vessels, our approach uses threshold technique which can change the threshold value according to the image property. However, in order to detect thin vessels, the proposed approach utilizes a basic line detection method incorporating a phase-preserving denoising technique, local normalization and maximum entropy. phase-preserving denoising method significantly removes the noise closer to the blood vessels and line detection methods detects the detailed blood vessel from the denoised image. Local normalization is further used to correct the remaining non-uniform illumination in an image. Our algorithm is efficient, computationally fast and evaluated with four publicly available databases: the DRIVE database (Niemeijer et al., 2004), the STARE database (Hoover et al., 2000), the CHASE_DB1 (Owen et al., 2009) and High-resolution fundus image (HRF) (Odstrcilik et al., 2013). The outcome of our method is compared with the recent results produced in the literature which confirms that our method outperforms the existing solutions.

Rest of the paper is structured as follows. A detailed review of the models used for retinal vessel segmentation is discussed in Section 2. Section 3 provides an explanation of the new proposed method. In Section 4, experimental results are analyzed and compared to the methods in the literatures. Section 5 concludes the work in the paper.

2. Overview of the approach

In the following section, we explain our motivations to use several different models for retinal vessel segmentation.

2.1. Retinal background estimation and subtraction

The important and primary pre-processing step in our algorithm is background estimation. This process normalizes and reduces the non-uniformed intensity distribution. The normalized image is obtained by the subtraction of background estimation from an inverted green image. The background estimation is acquired by performing a morphological opening operation. The normalized image is computed using Eq. (1)

$$I_1 = I_g - I_{bg} \tag{1}$$

where I_1 labels normalized images, I_g labels inverted green images and I_{bg} labels background estimations. The background estimation satisfies Eq. (2):

$$I_{bg} = \cup\left\{ (S_e) \mid (S_e) \subseteq I_s \right\}, \tag{2}$$

where S_e indicates a disc shaped structuring element with radius of R, I_s is the set of I_g and $\cup$ denotes union of set. The background estimation I_{bg} is given by geometric interpretation where unions of all translations of structuring elements S_e fit the entire image I_g. Therefore, the size of S_e must be estimated such that its value is larger than the width of the blood vessel. The width of the vessels is not likely greater than 15 pixels as per our observation, so we have considered the size of S_e as 15.

2.2. Local phase-preserving denoising of retinal images

Denoising process involves transformation of noisy images into some domain where noise components are more easily recognized. To remove noise, a thresholding procedure is implemented and the transformation is reversed to reconstruct a noise-free image. The denoising method is associated with a complex valued log Gabor wavelet filter where amplitude information is decomposed while preserving important phase information of an image (Kovesi, 1999). The process begins with calculating amplitude and local phase data at each point of a retinal image. This is performed by utilizing log-Gabor wavelet filter (Fischer et al., 2007) that has a Gaussian transfer function viewed on a logarithmic frequency

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