A Review of Algorithms for Retinal Vessel Segmentation

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***Abstract*—This paper presents a review of algorithms for extracting blood vessels network from retinal images. Since retina is a complex and delicate ocular structure, a huge effort in computer vision is devoted to study blood vessels network for helping the diagnosis of pathologies like diabetic retinopathy, hypertension retinopathy, retinopathy of prematurity or glaucoma. To carry out this process many works for normal and abnormal images have been proposed recently. These methods include combinations of algorithms like Gaussian and Gabor filters, histogram equalization, clustering, binarization, motion contrast, matched filters, combined corner/edge detectors, multi-scale line operators, neural networks, ants, genetic algorithms, morphological operators. To apply these algorithms pre-processing tasks are needed. Most of these algorithms have been tested on publicly retinal databases. We have include a table summarizing algorithms and results of their assessment.**

***Index Terms*—fundus, fundus analysis, image analysis, morphology, retinal vessels segmentation, retinopathy, vessel detection.**

I. Introduction

THE blood vessels of the retina are a complex network. The assessment of retinal vascular network is basic for various medical diagnoses, such as retinopathy caused by diabetes, retinopathy caused by hypertension, glaucoma or retinopathy of prematurity (ROP). Automatic extraction of the retinal vasculature can assist to the doctors in the implementation of screening programs for retinopathies. The measure of the state of retinal vessels network allows to do other characterizations for each kind of pathology. For example in ROP diagnosis, the severity level and the tortuosity index are based on percentage of well-formed network. There are several automated and semi-automated proposals to do it [1].

The examination of the retina encloses a fundus exam, generally do it with high definition ophthalmology camera, for example RetCam (Clarity Medical Systems Inc., Pleasanton, CA, USA). Though, there are hospitals or complete populations where they do not have this kind of sophisticated equipment. They should diagnosis with bad quality image or video. Some algorithms have been designed and tested for those kind of images too.

The input for algorithms are fundus color images and the requirement is to be able to classify each pixel as vessel or non-vessel and give an output image with the blood vessels network. For doing this complex task, researchers use and improve many algorithm like Gaussian and Gabor filter, histogram equalization, clustering, binarization, motion contrast, matched filter, combined corner/edge detector, multi-scale line operator, neural network, ant, genetic, morphological operators. Combined algorithms create one method to obtain successful results.

Methods have been tested in databases with more than 20 images. Some of the databases are available freely, for example DRIVE and STARE [2] and REVIEW [3]. Results have been quantified in terms of sensitivity (True Positive) and graph under ROC curve [4].

There are a large number of works for segmenting the blood vessel from retina image. In this article, we present the last and relevant papers (publications of year 2014 and relevant papers of prior years). We have also studied past researches based on previous papers review [5]- [6].

This paper is organized as follows: In Section II, we described recently and relevant works. Then, a discussion is presented in Section III. At last, we conclude this paper in Section IV.

II. Algorithms for Segmentation

A set of relevant article ordering by date are described. A summary of those descriptions is in table I.

In 2014, a method for extracting retinal blood vessels using an optimized Gabor filter is presented [7] . The Gabor filters are a set of orientation and frequency sensitive band pass filters which have the optimal localization in both the frequency contents of the patterns [8]. This proposal starts with a RBG (red, blue, green) retinal image, like pre-processing tasks they extract green channel, apply an adaptive histogram

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equalization, and convert to grayscale and binary image. They used [3×3] size of median filter to reduce the salt & paper noise, and length filter is used to remove isolated pixels by using concept of connectivity in binary image. They quantified the results by true positive and false negative. They compared its proposal with other four proposals and they got accuracy equal to 97.72%, better than other ones.

An unsupervised classification method by finding patterns of blood vessels in retinal images is proposed in [9]. That patterns are used to determine whether a pixel belongs to a vessel or not. Before that, a morphological top-hat transform [10] is applied for improving contrast of the retinal image. This method was tested over two publicly databases DRIVE [2] and REVIEW [3]. Results were compared with related works.

Matched filter techniques are widely used for the detection of blood vessels [11]. In [12], three technics are combined for segmenting all vessel network of retinal images. Images are acquired in video format, with an Adaptive Optics scanning laser ophthalmoscope (AOSLO). A motion contrast is used to get a single image from all the division images. Multi-scale matched filter (MF) method is applied to distinguish vessels and false edges. After that, they applied the combined corner/edge detector to eliminate the effect of motion artifacts. And finally they did a dilation for restoring the contour of vessels. That techniques were tested in 89 AOSLO images (available from the University of California, Berkeley).

A method to detect retinal vessels in normal and abnormal fundus images is proposed in [13], this method is based on vessels linear features and implement multi-scale line operator. A line detector which is based on the evaluation of the gray intensity average along lines of fixed length passing through the target pixel at different orientations is applied to the green channel of an RGB image and the response is thresholded to obtain unsupervised pixel classification. This method is evaluated on two public databases STARE and DRIVE [2].

In [14], retinal blood vessels are identified by using a multilayer perceptron neural network. Input images are color fundus, they are pre-processed by eliminating the hue and saturation information, retaining the luminance and converting to grayscale images. Then, grayscale images are smoothened using Gaussian filters and vectors features are obtained applying Gabor filter. These vectors classify each pixel like vessel or non-vessel. The set vessels is given as input to neural network training. A back propagation algorithm is applied in the neural network. DRIVE database is used to assessment. True positives reported 99%, and false positive 50% in highest wrong cases.

In [15] the segmentation of blood vessels in a pre-processed image utilised a MF approach. B-spline-based illumination correction method and contrast enhancement were used as pre-processing tasks over green channel of the original input image. Matched filter cross-sectional profiles were heuristically classified into five classes of differing blood vessel thicknesses, their objective was achieve a reliable and precise detection of all possible blood vessel segments with an acceptable width resolution. This method was tested in public DRIVE and STARE databases [2].

Ant-based approaches had been applied in edge detection [16]-[22]. Based on that previous state-of-art, a combined model of matched filter and ant colony algorithm is proposed in [23]. Ant parameters (number of ants, iteration and memory sizes) are taken from prior empirical work. Ant algorithm

TABLE I
SYNOPSIS OF PROPOSALS

Ref.	Year	Techniques/ Algorithms	Accuracy/ Effectiveness	ROP Assessment	Pre-processing	Input Image
[7]	2014	Optimized Gabor filter, histogram equalization. Image format conversion.	Accuracy: 99.72 % Sensitivity: 98.15%	No	Yes	2D
[9]	2014	Unsupervised classification, spectral clustering, entropy-based binarization.	Accuracy: 94.44%	No	Yes	2D
[12]	2014	Motion contrast method, matched filter, combined corner/edge detector, morphological dilation.	---	No	Yes	2D
[13]	2014	Multi-scale line operator, Weber's law, k-means clustering. Image format conversion.	Accuracy STARE: 94.83% AUC STARE: 94.31% Accuracy DRIVE: 93.87% AUC DRIVE: 93.03%	No	Yes	2D
[14]	2014	Back propagation neural network, Gaussian and Gabor filters. Image format conversion.	True Positive: 99% False Positive: 50%	No	Yes	2D
[15]	2013	Matched filter, B-Splane illumination correction, contrast equalization, thresholding.	Healthy-Img. SE: 78.61% SP: 97.50%; ACC: 95.39%; AUC: 97.42% DR-Img. SE: 74.86% SP: 96.19%; ACC: 94.45%; AUC: 95.82%	No	Yes	2D
[23]	2009	Ant, Matched filter. Image format conversion.	--	No	Yes	2D
[25]	2007	Genetic algorithms (Encoding, fitness function) - Gaussian matched filter. Image format conversion.	MAA DRIVE: 94.22% AUC DRIVE: 95.82%	No		2D
[26]	2006	Morphological operators: maximum of openings, reconstruction by dilation, threshold by hysteresis. Image format conversion.	---	No	Yes	2D

AUC: area under the ROC curve; ACC (Accuracy); SE (Sensitivity): True Positive rate; Selectivity: False Positive rate; SP (Specificity); These metrics are described in [4] . DR diabetic retinopathy. DRIVE: publicity database of normal retinal images. STARE: publicity database of pathological retinal images.

includes exploration of vessels using marked blocks, merging blocks and binarization. Match filter consist of green channel normalization, LogSig scaling and Gaussian filtering to find vessels [11]. The ant algorithm result is combined with matched filter for getting a previous resultant image. Finally, length filtering is applied over that previous image and vessels are achieved.

Genetic algorithms operate on a set of individuals called population, where each individual is an encoding of the input problem data and are called chromosomes. Each fitness individual is calculated using an objective function. One iteration of the search is called a generation. From each generation the fittest individuals are selected and pooled out to form a base for a new population with better characteristics. Genetic algorithms are characterized by attributes such as objective function, encoding of the input data, crossover, mutation, and population size [24]. In other hand, as we mentioned above matched filter techniques are widely used for the detection of blood vessels. In [25], genetic algorithms have been used for choosing best parameters to Gaussian matched filter and give a better approach in comparison with empirical estimation. The results showed better assessment.

A set of morphological operators are used to extract the skeleton of the vascular network from fundus color image in the proposal [26]. First, a grayscale image was obtained from the fundus green channel, next the maximum of openings [27], [10] operator is applied for diminishing noise and getting a uniform background. The extraction of skeleton is made in two processes: sum of valleys (first approximation and noise artefacts), and thresholding by hysteresis and a reconstruction by dilation [10]. This proposal was not assessment or compare with another methods.

Previous similar reviews are: in 2004, in [5] is published a large review that classifies the algorithms in eleven categories. A complete state-of-art until 2011 is presented in [28]. In [6] can see a short survey that presents advantage and limitations of the methods founded until 2012.

III. Discussion

To perform this work, we made a systematic review exploring in three major search engines (web of science [29], ieeexplorer [30], scholar google [31]). First, the results have been filtered by a previous year and ordered by relevance. Next, we read the abstract of each article and we performed a selection of the best works for the full reading. Finally, we proceed to decide whether to include or discard the article from the survey.

Typical edge detection techniques, such as Sobel operator, Canny border detector, and Prewiit operator [32] are not appropriate for vessel detection. We have revised several combination of algorithm (ant, genetic, clustering, match filtered, mathematical morphology) for the retinal vessels extraction. So, we can say that it is necessary more than one processing algorithm to acquire acceptable results, and before to segment the image it is convenient to do pre-processing tasks. In comparison with the manual labelled and segmentation, in manual process experts do not need pre-processing but it is a harder task. In order to test automatic methods there are some databases with labelled images [2].

Most methods detect vessels in normal retina images well, but they do not have any procedure to cope with lesions on images of abnormal retinas. In order to resolve it, more pre-processing tasks are required.

One common pre-processing task, is to obtain grayscale image from the green channel. Generally, blood vessels are darker than the background, although there are areas where the vascular network is not visible because its level is similar to the background. Several studies showed green channel save the best pixel information. Contrast enhanced is another of the most common pre-processing task, is did it in both healthy and pathological retinal images.

About the results, true positive cases are over 90%, but we note three points: in medicine we need to achieve 100% in both true positives and false negatives cases, and that they must work in bad quality images well.

IV. Conclusions

The set of algorithms studied reveals that to improve automatic segmentation of retinal vessels it is necessary to pre-process images and create segmentation methods by combination. This requirement has been a venue of research by itself in the last decade.

Pre-processing tasks are required before applying segmentation algorithms. The most common ones are contrast enhanced, extraction of green channel and convert to grayscale image. Also, since most cases algorithms working on grayscale intensity, users can convert to color image again after the process.

Best results are obtained in healthy retinal image. It seems that more research is needed over pathological retinal images and bad quality images. On the one hand, improving results on pathological retinal image is a mandatory goal for supporting medical diagnosis. On the other hand, improving results in bad quality images is an objective to achieve for populations where neither expensive nor sophisticated ophthalmology cameras are available.

In order to share the latest findings and help to real diagnosis this kind of algorithms could be part of a telemedicine system. Also, it could be available on the internet cloud.

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