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Vessel Segmentation in Retinal Images using Graph-Theoretical Vessel Tracking

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Abstract

This paper presents a method for automatic segmentation of blood vessels in retinal images. The method is based on vessel tracking technique. The key idea of the method is that first a set of seed points (center of vessel cross sections) is extracted. Then, the seed points are connected to establish the vessel skeleton. Finally, the false vessel point are rejected by resorting to a hypothesis-verificaton based procedure. The major contribution of this work is that we formulate the step of seed point connection in the form of graph-theoretical shortest path problem. Then we apply the Dijkstra's algorithm to solve the problem. The performance of our method evaluated on the publicly available DRIVE database shows promising results.

1 Introduction

Several diseases in retinal vasculature e.g. diabetes, hypertension, and arteriosclerosis can be diagnosed by observing some retinal vessel characteristics e.g. calibre, color, tortuosity, etc. To aid ophthalmologists during diagnostic and treatment processes, many algorithms were developed to extract blood vessels in retinal camera images.

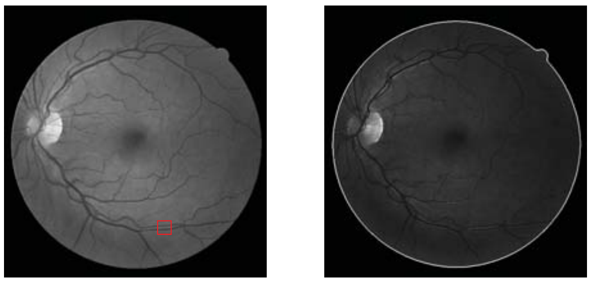
The techniques for automatic segmentation blood vessels are roughly divided into four categories [2]. The first one is based on supervised learning technique [10, 11] in which each pixel of a testing retinal image is classified as either *Vessel* or *Non-Vessel*. The second category is to apply the matched filtering technique to a retinal image [8, 9]. Then the vessels can be detected from the resulting convolved image. For the third category, the techniques based on mathematical morphology [12, 13] are proposed. The last category is based on tracking vessels from a set of candidate seed points [3, 5, 6, 7]. The common idea among these works can be explained as follows. First, a set of pixels, refer to as seed points, are extracted in the area of retinal vessel center. This can be achieved by several methods such as matched filters, morphological filters, optimization of Gaussian profiles or fuzzy c-mean classifiers. Then some heuristic procedures are applied to connect the detected seed points into vessel skeleton. Finally actual vessel are extracted by analyzing the 1D intensity profile of vessel cross section around the seed points.

Our proposed method lies into the forth category mentioned above. Specifically speaking we proposed to tackle the seed point connection stage with more elegant mathematical framework instead of relying on heuristics. That is we formulate the problem in the form of graph-theoretical shortest path problem. The solution is achieved by applying Dijkstra's algorithm [14]. The obtained solutions reflect more sensible seed-point connected paths in which finally they are turned into decently extracted vessels.

The remainder of the paper is outlined as follows. In section 2, we elaborate on the data set that we use to evaluate our method. In section 3, we explain in detail about our proposed method. In section 4, we show the results evaluated on the *DRIVE* database. Finally the conclusion is drawn.

2 The Proposed Method

Our proposed method can be divided into 3 consecutive stages referred to as *seed point extraction*, *connection*, and *vessel verification*. The details of these stages can be explained as follows. Note that, in this work, the green channel of a color retinal image, as shown in Fig. 1(a), is used in the segmentaiton. This is because the green-channel image usually presents the highest contrast between regions belonging to the vessels network and the background.



(a) (b)

Figure 1. Retinal image of the *DRIVE* database: (a) green channel of a retinal image, (b) high-boost image of green channel.

2.1 Seed Point Extraction

In this step the candidate seed points are extracted. These seed points are used to bootstrap the rest of the method. Strictly speaking, a seed point is a pixel that lies in the vicinity of vessel center.

The procedure of seed point extraction can be explained with Fig. 2 as follows. A window of size $W \times W$ pixels is scanned through the whole image. The sub-image Fig. 2(a) in each scanning window is first applied with median filtering to reduce salt&pepper noises. Then the Canny edge detection is applied to extract the pixels that are potential to be vessel borders. The gradients of the detected edge points Fig. 2(c) will be used to extract seed points. Fig. 2(d) shows the zoom in of the gradients of the pixels in the drew rectangle of Fig. 2(c). Given an edge point, we scan along the line projecting from the edge point in direction specified by is gradient orientation. As scaning, we search for the corresponding edge point that is closeset to the projected line and their gradient orientations are pointing in the opposite direction.

The extracted seed points could consist of both the points corresponding to the vessel and the non-relevant points. Our method presented in the later stages can be reject those non-relevant points.

2.2 Connection

The goal of this step is to find a set of connected points originated from the seed points. These connected points represent the segmented vessel skeleton. Most of previous works [3, 4] tackle this step by relying on heurisctics. For example, Grisan et al [3] exploited a greedy-algorithmic based method to connect the points by using local information around those points.

In this work, we propose to formulate the problem of connecting points in the form of a graph-theoretical shortest path problem. And then we apply Dijkstra's algorithm to solve for the solution of the graph problem. The optimal solutions obtained is the resulting connected paths. The details of this step can be explained as follows. First, we apply connected component analysis to the set of extracted seed points. This yields to a set of connected points. Each set represents a fragment of vessel skeleton. As mentioned earlier, a seed point obtained from the previous step could correspond to either vessel or non-vessl relevant point. We consider the connected point sets whose sizes are less than a small value (e.g. 5-7 points) as non-vessel and then they are rejected.

Now, our task for the connection step is aimed at finding suitable paths in the image coordinate space that establish connections among the end-points of the connected sets. The meanings of connected point set and end-point can be depicted in Fig. 3. For each end-point, our method will search for the paths connecting to other end-points in the neighborhood area. For finding the connection path between each pair of end-points, we construct an undirected graph $G = \{V, E\}$ in which the nodes V are the set of the pixels in neighborhood area and an edge between two nodes is established if their pixels are in 8-neighbor locations of each other, see Fig. 3.

The weight of an edge is defined by using the pixel values of the high-boost image (Fig. 1(b)). The reason to use the high-boost image is to incorporate into the weight with the terms reflecting to both intensity and difference of intensity. Specificaly speaking, the edge's weight between node i and node j, i.e. $W_{i,j}$, is assigned with the pixel value corresponding to node j in the high-boost image that can be defined as

$$W_{i,j} = I_j^2 \; + \; k \times |G_j|^2 \tag{1}$$

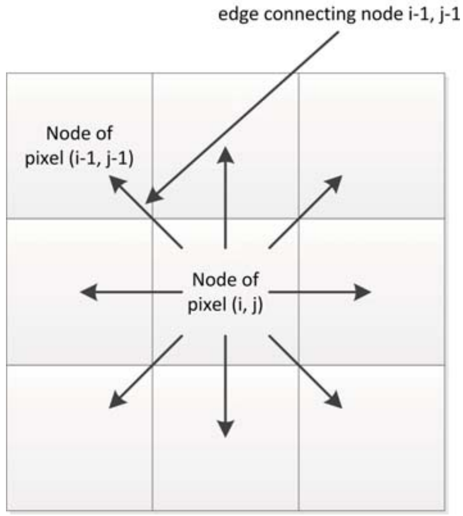


Figure 3. Path of the graph oreinted of node i

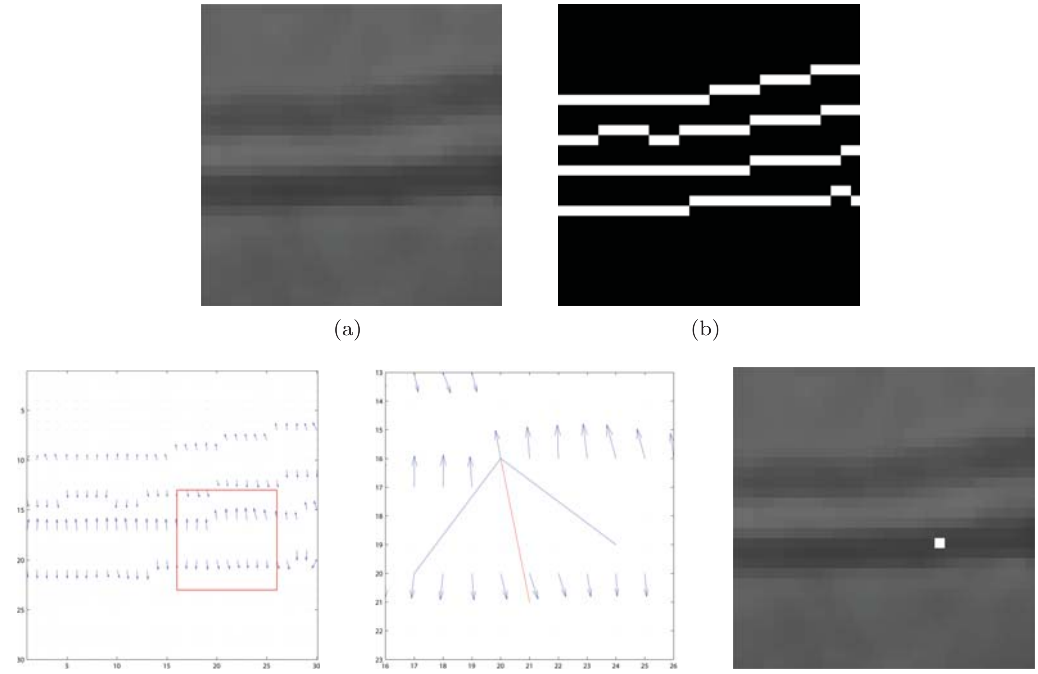
where I_j and $|G_j|$ are the intensity and the gradient magnitude of pixel j, respectively. And, k is a constant value used to balance the effect of intensity and the effect of intensity difference. In this work, k is set to a value in the range 20-25.

After the graph is created, we apply the Dijkstra's algorithm where the nodes corresponding to the end-points are specified as the source and destination nodes. The shortest paths obtained and the sets of connected points are considered as the connected points that establish the vessel skeleton. Some examples of the result of this step can be shown in Fig. 5(b).

2.3 Vessel Verification

The connected point set obtaind from the previous step may still contain non-vessel points. In the final step of our proposed method, the vessel verification module is used to remove these non-vessel points. The hypothesis to be verified is based on the key idea that the intensity profile along the cross section of a point corresponding to vessel skeleton will have intensity changes from background to foreground and then from foreground to background. An example of intensity profile that has vessel points can be shown Fig. 4. In the figure the profile contain two vessel points each point corresponding to the local minimum of the profile.

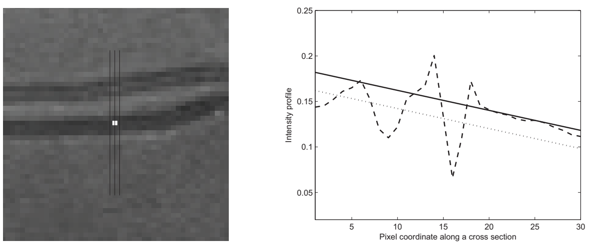
The procedure to decide whethere a point is vessel can be explained as follows. First the perpendicular profile of the point and two profiles of the consecutive points (preceding and succeeding points) are averagely combinded into a single intensity profile. The intensity of the background level in the averaged profile is approximated with a straight line equation using an robust M estimator [15] as shown with the solid line in Fig. 4(b). If the intensity of the hypothetical point is below the value of aprroximate stright line, we consider the point as vessel. Otherwise the point is considered as non-vessel and is rejected.



(a) (b)

(c) (d) (e)

Figure 2. Seed point extraction: (a) sub-image, (b) edge of subimage, (c) gradients of the detected edge points, (d) gradients in the rectangle region from (c), (e) seed point (white pixel).



(a) (b)

Figure 4. (a) vessel image with selected three cross sections, (b) cross section intensity profile average (dash-dash line), intensity profile approximation (solid line), and threshold value (dot-dot line).

3 Results and Discussion

We show the performance of our proposed methods with qualitative results. In our experiment we use publicly available retinal image database referred to as DRIVE (Digital Retinal Images for Vessel Extraction at http://www.isi.uu.nl/Research/Databases/DRIVE) [1]. Each image is a color retinal fundus images acquired by a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Due to space limitation, we show some selected results of the segmented vessel skeleton obtained from our method in Fig. 6. The pictures on the first row show the results obtained after the vessel verification. While the pictures on the next row show the same results plotting on the groundtruth images (provided by the database creators). As you may observe from the above pictures, our methods can detect most of the major parts of vessel skeleton (1.22 % false positive). Futhermore the picture in Fig. 5(b) shows that our graph-theritical based approch can fill the gap between the point sets. Also the picture in Fig. 5(d) shows how the vessel verifier can remove non-vessel points.

Our proposed method still have some drawbacks that need to do more research in future. Some of these drawbacks can be listed as follows. First our method still can not robustly handle the connections of bifucations and crossings. However this problem can be improve by incorporating more extensive hypotheses about the vessel around bifurcations and crossing areas. Optionally one may want to get the complete segmented vessel in the retinal images (the results similar to the groundtruth). Our work produces only the vessel skeleton. Nevertheless our method can be simply extended to obtain such results by applying region growing around the skeleton points.

4 Conclusion

In this work, we present a method to segment the retinal vessel in images. The output of the method is in the form of vessel skeleton. The method starts with the extracton of vessel seed points. Then a graph-theoritical shortest path based techinque is apply to connect the seed points. Finally the vessel verification based on intensity profile analysis is exploited to remove false vessel skeleton points. The qualitative results on *DRIVE* retinal images show promising results. The work left to do in future is mainly to handle the cases of bifurcations and crossings.

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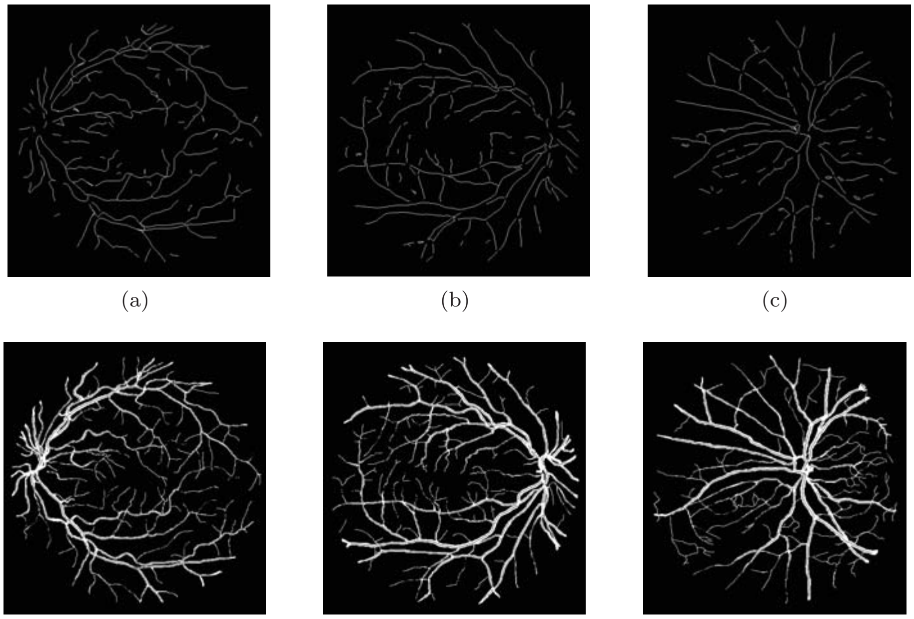
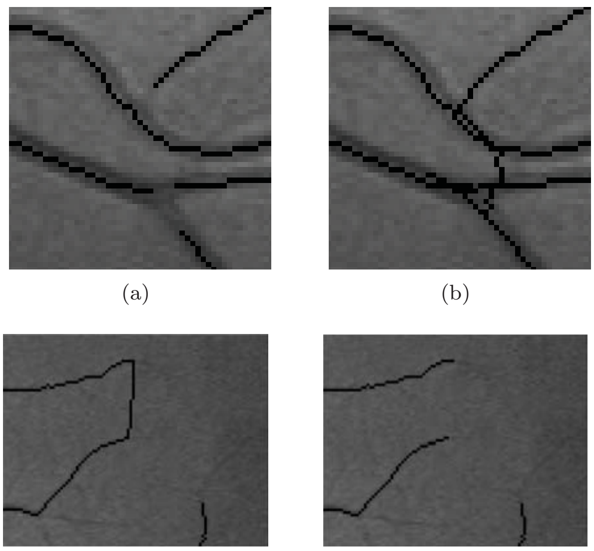


(a) (b) (c)

(d) (e) (f)

Figure 6. First row is the result from our method, next row is results plotting on the groundtruth images



(a) (b)

(c) (d)

Figure 5. (a) the result from seed point extraction (b),(c) after apply Dijkstra's algorithm (d) after apply vessel verification.

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