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Research Article

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Detection of blood vessel Segmentation in retinal images using Adaptive filters

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ABSTRACT

In biomedical imaging analysis and computer-assisted diagnosis, segmentation analysis is an intense field of research and development. The most difficult part of medical image analysis is the automated localization and delineation of structures of interest. Automated data evaluation is one way of enhancing the clinical utility of measurements. In particular, medical image segmentation extracts meaningful information and facilitates the display of this information in a clinically relevant way. Segmentation of blood vessels in retinal images allows early diagnosis of disease; automating this process provides several benefits including minimizing subjectivity and eliminating a painstaking, tedious task. This paper, addresses the problem of automatically identifying true vessels as a post processing step to vascular structure segmentation. The segmented vascular structure is modeled as a vessel segment graph and formulates the problem of identifying vessels as one of finding the optimal forest in the graph given a set of constraints. A method is designed to solve this optimization problem and show that the proposed approach is able to achieve good pixel precision and recalls all true vessels for clean segmented retinal images, and remains robust even when the segmented image is noisy.

Keywords: Adaptive Median Filtering, Histrogram Equalization, Entropy Filtered Image, Erosion, Dilation

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INTRODUCTION

Measurements of retinal blood vessel morphology are related to the risk of cardiovascular diseases. The wrong identification of vessels may result in a large variation of these measurements, leading to a wrong clinical diagnosis. This paper, addresses the problem of automatically identifying true vessels as a post processing step to vascular structure segmentation. The segmented vascular structure is modeled as a vessel segment graph and formulates the problem of identifying vessels as one of finding the optimal forest in the graph given a set of constraints. A method is designed to solve this optimization problem and show that the proposed approach is able to achieve good pixel precision and 98% recall of the true vessels for clean segmented retinal images, and remains robust even when the segmented image is noisy.

In the context of biomedical imaging analysis and computer-assisted diagnosis, segmentation analysis is an intense field of research and development. The most difficult part of medical image analysis is the automated localization and delineation of structures of interest. Automated data evaluation is one way of enhancing the clinical utility of measurements. In particular, medical image segmentation extracts meaningful information and facilitates the display of this information in a clinically relevant way. A crucial role for automated information extraction in medical imaging usually involves the segmentation of regions of the image.

Segmentation of blood vessels in retinal images allows early diagnosis of disease; automating this process provides several benefits including minimizing subjectivity and eliminating a painstaking, tedious task. Previous approaches, while satisfactory in some cases, still leave room for improvement, especially in abnormal retinal images. These works sets to remove noise, enhance the image, and track the edges of the vessels and also proposes graph tracer algorithm to find difference between vessel bifurcations and vessel crossover.

This paper deals with identifying all true vessels from segmented retinal image. Before finding true blood vessels image is processed first. Image-processing operations transform the grey values of the pixels. There are three basic mechanisms by which this is done. In its most simple form, the pixels grey values are changed without any processing of surrounding or 'neighbourhood' pixel values. Neighbourhood processing incorporates the values of pixels in a small neighbourhood around each pixel in question. Finally, transforms are more complex and involve manipulation of the entire image so that the pixels vales are represented in a different but equivalent form. This may allow for more efficient and powerful processing before the image is reverted to its original mode of representation. The aims of processing of an image normally fall into one of the three broad categories: enhancement (e.g., improved contrast), rest oration (deblurring of an image), segmentation and all true vessels from segmented retinal image.

LITERATURE SURVEY

A semi-automatic method to measure and quantify geometrical and topological properties of continuous vascular trees in clinical fundus images is described. Measurements are made from binary images obtained with a previously described segmentation process. The skeletons of the segmented trees are produced by thinning, branch and crossing points are identified and segments of the trees are labeled and stored as a chain code. The operator selects a tree to be measured and decides if it is an arterial or venous tree[1].

An automatic process then measures the lengths, areas and angles of the individual segments of the tree. Geometrical data and the connectivity information between branches from continuous retinal vessel trees are tabulated. A number of geometrical properties and topological indexes are derived. Vessel diameters and branching angles are validated against manual measurements and several derived geometrical and topological properties are extracted from red-free fundus images of ten normotensive and ten age- and sex-matched hypertensive subjects and compared with previously reported results[2].

This [3] paper presents an algorithm for segmenting and measuring retinal vessels, by growing a ldquoRibbon of Twinsrdquo active contour model, which uses two pairs of contours to capture each vessel edge, while maintaining width consistency. The algorithm is initialized using a generalized morphological order filter to identify approximate vessels centerlines. Once the vessel segments are identified the network topology is determined using an implicit neural cost function to resolve junction configurations. The algorithm is robust, and can accurately locate vessel edges under difficult conditions, including noisy blurred edges, closely parallel vessels, light reflex phenomena, and very fine vessels. It yields precise vessel width measurements, with subpixel average width errors. We compare the algorithm with several benchmarks from the literature, demonstrating higher segmentation sensitivity and more accurate width measurement [4-6].

This paper [7] presents an automated method to identify arteries and veins in dual-wavelength retinal fundus images recorded at 570 and 600 nm. Dual-wavelength imaging provides both structural and functional features that can be exploited for identification. The processing begins with automated tracing of the vessels from the 570-nm image. The 600-nm image is registered to this image, and structural and functional features are computed for each vessel segment. The relative strength of the vessel central reflex is used as the structural feature. The central reflex phenomenon, caused by light reflection from vessel surfaces that are parallel to the incident light, is especially pronounced at longer wavelengths for arteries compared to veins. Dual-Gaussian is used to model the cross-sectional intensity profile of vessels [8].

EXPERIMENTAL SECTION

The proposed method aims to identify vessels and represent them in the form of binary trees for subsequent vessel measurements. Proposed method aims at processing the given image and identify crossover and search for optimal forest.

It has two main steps:
- Identify crossovers,
- Search for the optimal forest (set of vessel trees).

Morphology *i*s a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.

ADAPTIVE MEDIAN FILTERING

Adaptive filters have are used in image processing for edge preserved image denoising and deblurring, image segmentation, and reliable object detection. In the talk, from a unified approach based on the ideas of signal local approximation, a family of linear and rank local adaptive filters for image restoration, segmentation and enhancement will be introduced. The filters work in a running window on the base of local spectral (DFT, DCT and others) features (local adaptive "linear" filters) or local first order statistics ("rank" filters) and, in each position of the window, generate an estimate of the central pixel of the window. They filters implement, as special cases, a broad variety of adaptive algorithms that can be exemplified by different modifications of local empirical Wiener and rejective filters, median, L- and selectable rank order filters, trimmed mead filters, local histogram modification filters, etc. Due to the existence of recursive algorithms for local spectral analysis in DFT, DCT and other bases, the computational complexity of local adaptive linear filters is proportional to the size of the window. The computational complexity of the rank filters may do not depend on the size of the window thanks to the recursive computation of local histograms and their parameters.

HISTOGRAM EQUALIZATION

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive.Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-color to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images.

Fig1 UnEqualized Image

Fig 2 Histogram Equalized Image

Generalizations of this method use multiple histograms to emphasize local contrast, rather than overall contrast. Examples of such methods include adaptive histogram equalization and contrast limiting adaptive histogram equalization or CLAHE. Histogram equalization also seems to be used in biological neural networks so as to maximize the output firing rate of the neuron as a function of the input statistics. Histogram equalization is a specific case of the more general class of histogram remapping methods. These methods seek to adjust the image to make it easier to analyze or improve visual quality shown in fig 1& 2.

ENTROPY FILTERED IMAGE

In the case of an image, these states correspond to the gray levels which the individual pixels can adopt. For example, in an 8-bit pixel there are 256 such states. If all such states are equally occupied, as they are in the case of an image which has been perfectly histogram equalized, the spread of states is a maximum, as is the entropy of the image. On the other hand, if the image has been thresholded, so that only two states are occupied, the entropy is low. If all of the pixels have the same value, the entropy of the image is zero shown in fig 3 & 4.

The *entropy H* of an image is defined as

$$H = -\sum_{k=0}^{M-1} p_k \log_2(p_k)$$ --(1)

where M is the number of gray levels and p_k is the probability associated with gray level k.

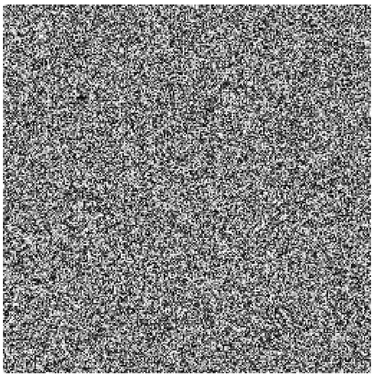


Fig 3 Entropy of 8 bits and is uncompressible

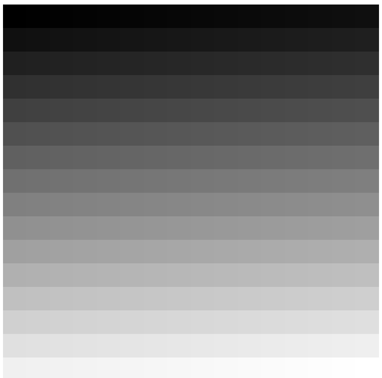


Fig 4 Distribution with highly spatially correlated

Maximum entropy is achieved in the case of a uniform probability distribution. If $M = 2^n$, then p_k is constant and given by

$$p_k = \frac{1}{M} = 2^{-n}$$ --------------------------------(2)

THRESOLDED IMAGE

In image processing, threshold is used to split an image into smaller segments, or junks, using at least one color or grayscale value to define their boundary. A possible threshold might be 40% gray in a grayscale image: all pixels being darker than 40% gray belong to one segment, and all others to the second segment. It's often the initial step in a sequence of image-processing operations shown in fig 5 &6.

Fig 5 Original Image

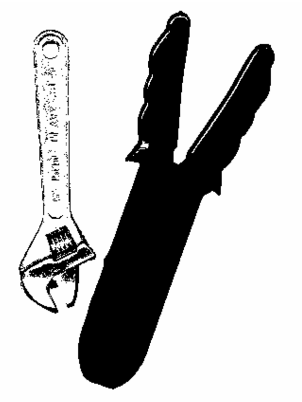


Fig 6 Thresholded Image

In case the object in the foreground has quite different gray levels than the surrounding background, image thresholding is an effective tool for this separation, or segmentation. Another important point is that usually no spatial characteristics are considered when calculating thresholding values.

DILATION OF BINARY IMAGE

The value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1.The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as dilation or erosion. This table lists the rules for both dilation and erosion.

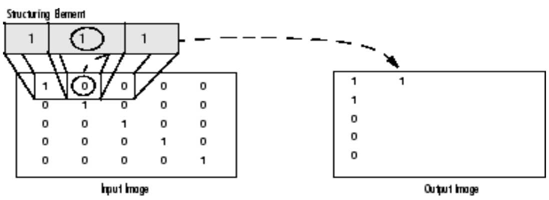


Fig 7 Dilation of binary image

The figure above (7) illustrates this processing for a grayscale image. The figure shows the processing of a particular pixel in the input image. Note how the function applies the rule to the input pixel's neighborhood and uses the highest value of all the pixels in the neighborhood as the value of the corresponding pixel in the output image.

THINNED IMAGE

Morphological functions position the origin of the structuring element, its centre element, over the pixel of interest in the input image. For pixels at the edge of an image, parts of the neighbourhood defined by the structuring element can extend past the border of the image. To process border pixels, the morphological functions assign a value to these undefined pixels, as if the functions had padded the image with additional rows and columns. The value of these padding pixels varies for dilation and erosion operations. Pixels beyond the image border are assigned the maximum value afforded by the data type. For binary images; these pixels are assumed to be set to 1. For grayscale images, the maximum value for images is 255.

SEGMENTED BLOOD VESSEL IMAGE

Identify Crossover Locations

Vessels in a retinal image frequently cross each other, at a point or over a shared segment. We call the former crossover points and the latter crossover segments. Crossover Point*:* Given the set of white pixels P in a line image, a junction $J \in JP$ is a crossover point if and only if the number of segments that are adjacent to J is greater than or equal to 4 .For example, the lower junction in Fig. 8 is a crossover point as it has four segments adjacent to it.

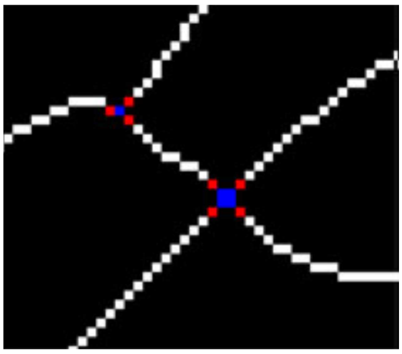


Fig. 8 Example of segment pixels with their end pixels , and junction pixels

A crossover segment occurs when two different vessels share a segment as shown in Fig. 9(a). Given the set of white pixels P of a line image, a segment $s \in SP$ is a candidat*e* crossover segment .Short segments between two junctions are not necessary true crossover segments, as shown in Fig. 9(b). Hence, we propose to use the directional change between adjacent segments and their pixel intensity values to differentiate crossover segments.

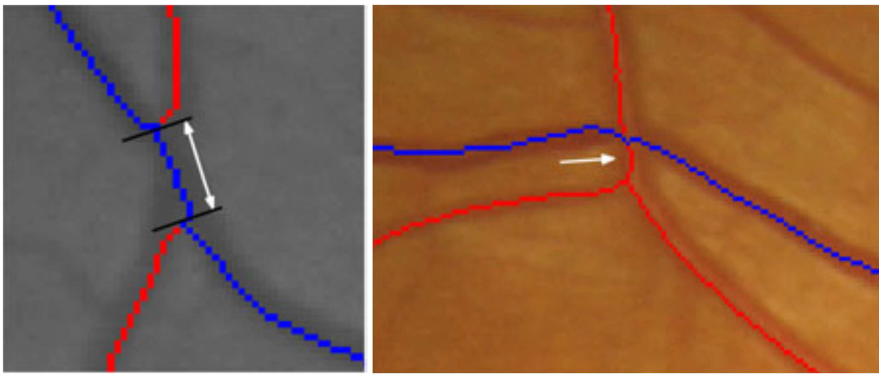


Fig. 9.Example crossover segment, point, and possible ambiguity. (a) Example of a crossover segment. (b) Example of a short segment between two junctions

Note that short segments between two junctions are not necessary true crossover segments, as shown in Fig. 9(b). Hence, we propose to use the directional change between adjacent segments and their pixel intensity values to differentiate crossover segments.

Fig 10 Blood vessels identified Finding Optimal Forest

The segments are modeled as a segment graph and use constraint optimization to search for the best set of vessel trees (forest) from the graph. Segment graph: Given the set of white pixels P in a line image, a segment graph GP = (SP ,EP), where each vertex in SP is a segment and an edge ei,j= (si, sj) ∈ EP exists if adj(si, sj), si, sj∈ SP , i = j. Typically, GP consists of disconnected subgraphs that are independent and can be processed in parallel. Without loss of generality, we refer to each of these subgraphs as the segment graph GP. The goal is to obtain a set of binary trees from the segment graph such that each binary tree corresponds to a vessel in the retinal image. Vessel: Given a segment graph GP =(SP ,EP), a vessel is a binary tree, T = (sroot, VT ,ET) such that's root is the root node, root(T) = sroot, VT ⊆ SP , and ET ⊆ EP . A set of such binary trees is called a forest. A binary tree is a natural representation of an actual blood vessel as it only bifurcates. Segment end points near the inner circle of the zone of interest are automatically identified as root pixels. The root of each tree corresponds to the root segment that contains a unique root pixel. Fig.10 shows the segment graph and two binary trees corresponding to the two vessels. The goal of simultaneous identification as a constraint optimization problem (COP) is formulated.

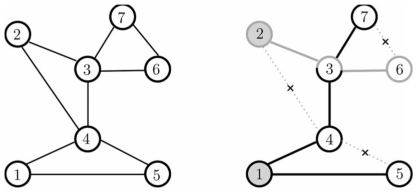


Fig 11 Segment graph corresponding to segments

The cost function on forests is defined as *cost*(*F*) =sums the average of the parent–child directional changes at bifurcations in *T*+ sums the change in direction between parents in the tree with only one child segment.

RESULTS AND DISCUSSION

Fig 12 Input Image

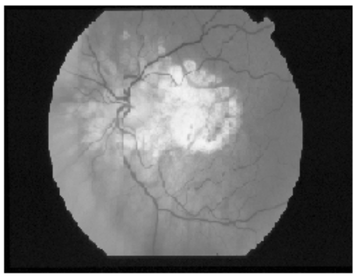


Fig 13 Gray Scale Image

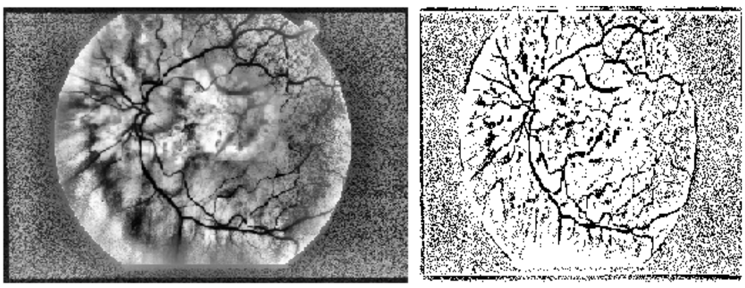
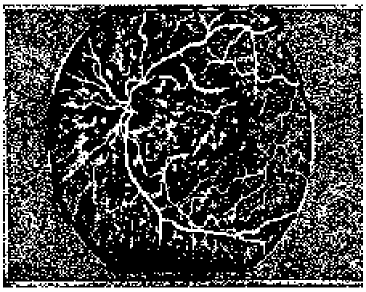


Fig14Adaptive Histogram Equalized Image



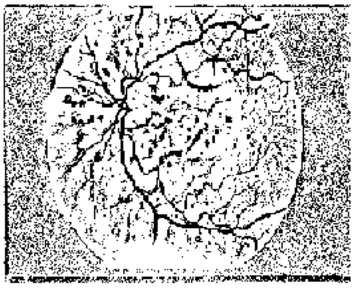


Fig 15 .Bottom Hat Image **Fig 16Black and White Image**

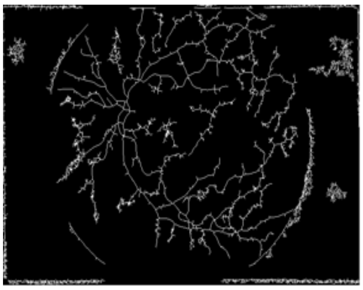


Fig 17 Segmented Vessel Binary Image

In the fig 12 Input images is given for blood vessel segmentation. Input image is converted into grey scale shown in fig 13. Histogram Equalization method increases global contrast of image. This allows for areas of lower local contrast to gain higher contrast shown in fig 14 Black and White Image obtained will highlight blood vessel for extraction shown in fig 15. Black and White Image obtained will highlight shown in fig 16. Area Opening Image Area Opening image will shown(fig 17) blood vessels for segmentation.

CONCLUSION

The proposed system allows processing of retinal image for identification of true blood vessels and cross overs in blood vessels. The method is based on vessel tracking technique. The key idea of the method is that first a set of cross over points (center of vessel cross sections) is extracted. Then, by using graph tracer algorithm optimal forest in retina is found and crossovers are identified. The major contribution of this work is to identify correct cross over point in blood vessel. The proposed method can be divided into 3 consecutive stages referred to as pre processing, identify crossovers, and identify blood vessel. Experiment results are analysed with respect to actual measurements of vessel morphology. The results show that the proposed approach is able to achieve 98.9% pixel precision .The system proposed does not provide any information on leakage of blood in retina. Future work deals with identification of damaged blood vessels in retina.

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