

AWN Classifier for Blood Vessels Extraction from Pathological Retinal Images

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Abstract

Automatic detection of retinal veins are particularly vital for the determination and the treatment of various visual maladies including diabetic retinopathy (DR), glaucoma and hypertension. Human retina is a wellspring of biometric framework which gives the most solid and stable methods for authentication. As the structure of retinal blood vessel is special it assumes a vital part in retinal biometrics. If there should arise an occurrence of anomalous retinal pictures with lesions, a few sores are likewise misdetected notwithstanding blood vessels. In this paper, we exhibit a novel technique to identify veins in the neurotic retinal images. The proposed technique comprises of three fundamental advances. The initial step is pre-preparing of retinal images to enhance the retinal pictures by assessment of a few image improvement procedures. In the second step an hybrid AWN classifier is used for detecting blood vessels. The performance of classifier is compared and analyzed on two publicly available databases (DRIVE and STARE) of retinal images using a number of measures, which include accuracy, sensitivity, and specificity.

Key Words: Retinal blood vessels, AWN classifier, authentication, STARE and DRIVE data base.

1. Introduction

Ocular fundus image can provide information on pathological changes caused by local ocular diseases and early signs of certain systemic diseases, such as diabetes and hypertension. For example, central retinal artery occlusion usually causes generalized constriction of retinal arteries, while central retinal vein occlusion typically produces dilated tortuous veins, arteriosclerosis can cause arteries to acquire a copper or silver color. Hypertension may result in focal constriction of retinal arteries, and diabetes can generate new blood vessels (neovascularization).[1]

Analyzing and interpreting retinal images have become a necessary and important diagnostic procedure in ophthalmology and considerable research effort has been devoted to automate this process. Among the features in ocular fundus image, the structure of retinal vessels plays an important role in revealing the state of diseases.[2] In addition, blood vessels can also serve as landmarks for image-guided laser treatment of choroidal neovascularization.[3] Thus, reliable methods of vessel detection that preserve various vessel measurements are needed.

Diabetic retinopathy is a complication of diabetes mellitus. It is the most common cause of blindness worldwide. Although diabetes itself cannot be prevented, complications such as blindness can be moderated if the disease is diagnosed early.[4] The most effective method currently is regular screening of the fundus to detect early signs of diabetic retinopathy. Microaneurysms – tiny dilations of the blood vessels—are the first unequivocal sign of diabetic retinopathy so that their detection in fundus images through photography might be enough to detect the disease in an early stage.[5] However, with a large number of patients undergoing regular screenings, tremendous amount of time is needed for the medical professionals to analyze and diagnose the fundus photographs. By automating the initial task of analysing the huge amount of retinal photographs for symptoms of diabetic retinopathy, the efficiency of the screening process can be greatly improved. At the same time, patients that require the attention of the ophthalmologist would be timely referred.

On the other hand, diabetic retinopathy resulting from long-term diabetes mellitus is one of the common diseases that lead to choroidal neovascularization (CNV). CNV is an important condition that leads to blindness. It decreases the amount of blood supplying the retina especially within the central area of acute vision. One treatment strategy is the use of lasers to photocoagulate the affected areas of the retina. To obtain satisfactory results, the physician must identify the full extent of CNV and cauterize it completely. Care must be taken to avoid radiating the macula (the area of acute vision), optic disc, and major blood vessels.

In the analysis of fundus images, two different types of the fundus images are used in term of the image capture procedure: retinal angiographies and normal fundus images. Images of retinal angiographies are obtained after an injection of fluorescein into the patients' arm. Retinal vessels are highlighted using an ultraviolet light. Photographs taken during the 5-min injection represents brighter blood vessels relative to a darker background (i.e., reversed contrast). The normal images are acquired using a fundus camera applied directly to the retina. In these images, the vessels are less contrasted than in angiographic images and they contain less information: small vessels are not obvious in the image. However, they are still very precise in accordance with the information contained in the image and widely used in retinal image analysis.

For both types of images, a charge coupled device (CCD) video camera is attached to the eyepiece of the fundus camera to make the images collected using the fundus camera available in standard image format. The output from the CCD camera is connected to a PC through image digitizer card. The retinal images were captured to the memory of the computer system. The images were saved on a hard disk for further processing. As for color retinal fundus image, the blue band appears to be very weak and does not contain much information. The vessels appear in red, however the red band usually contains too much noise or is simply saturated since most of the features emit a signal in the red band.

On the other hand, the green component of color fundus image gives the blood vessels on a highly contrasted background(darker blood vessels on a bright background). Hence, the green channel of the image is employed in the automated analysis of ocular fundus images. Data about veins can be utilized as a part of evaluating malady seriousness or as a component of the procedure of mechanized analysis of illnesses with visual appearances. Veins can go about as points of interest for confining the optic nerve, the fovea (focal vision territory), and sores. Because of foundational or nearby visual ailment, the veins can have quantifiable variations from the norm in breadth, shading, and tortuosity. For instance, focal retinal supply route impediment more often than not causes summed up narrowing of retinal courses, hypertension may bring about central tightening of retinal corridors, focal retinal vein impediment normally delivers expanded convoluted veins, arteriosclerosis can make the conduits procure a copper or silver shading, and diabetes can create fresh recruits vessels (neovascularization). In this manner, a solid technique for vessel discovery is required, which jam different vessel estimations.

2. Related Work

Recently some studies performed contour detection using deformable models has been shown to provide more accurate results. Nevertheless, it is not suitable for real-time applications because of its computational complexity and requires user interaction. N. H. Solouma *et al* [6]. propose an algorithm that extracts the

blood vessel tree accurately using deformable models and 1-D Gaussian filter with efficient computation. First, the boundaries of vessels are obtained using a simplified form of deformable models. The image is convolved by a Sobel operator in both the horizontal and vertical directions resulting edge values to represent the external energy of the contour. All the neighbouring points of each contour point are searched and points having a value above a certain threshold are extracted as new points on the contour. This process not only deforms the contour but also makes it grow. During the contour iteration, the seed contours that lie within the areas of poor edges shrink until vanishing while the others merge and/or split until recovering a continuous description of all edges that pass above a certain threshold. This process is repeated until no changes occur during a given iteration. Small vessels and the boundaries of large vessels are detected. Then, the core of the wide vessels is determined by correlating the image by a one-dimensional (1-D) Gaussian filter in two perpendicular directions. This reduces the computational complexity of the 2-D matching technique to a great extent and makes it practical for clinical applications.

Tracking: Zhou, et al. [7] develop an algorithm to track the midline and extract diameters and tortuosity of a single vessel segment, although only diameter measurements are reported. The tracking of a blood vessel proceeds by extending the search in the direction of the last-tracked part of the blood vessel by a certain fixed length. The density profile on the perpendicular line in the extended direction is taken and a Gaussian matched filter is convolved with it and the result is examined. The strategy is to estimate the next location based on the current location, observe the next actual location by the matched filter, correct the estimation and then re-estimate the next location and continue iteratively. Moreover, the matched filter helps ignoring small branches at a bifurcation point without any special handling, thus allowing the tracking process to follow one major branch continuously. However, the algorithm needs starting and ending points and a tracking direction defined by an operator.

Liu and Sun[8] present an approach that extracts extended tracts of vasculature in X-ray angiograms by an adaptive tracking algorithm. Given an initial point within a vessel, they apply an “extrapolation update” scheme that involves the estimation of local vessel trajectories. Once a segment has been tracked, it is deleted in the angiogram image by growing the “deletion intensity value” over the grey levels representing the vessel. This procedure is performed recursively to extract the vascular tree. This algorithm also requires the user to specify vessel starting points.

In L. Gang and O. Chutatape,[9] the fitness of estimating vessel profiles with Gaussian function is evaluated and an amplitude modified second-order Gaussian filter is proposed for the detection and measurement of vessels. It proves that the vessel width can be measured in linear relationship with the “spreading factor” of the matched Gaussian filter when the magnitude coefficient of the Gaussian filter is suitably assigned. The vessel width

measurement not only provides the size of blood vessel but it is also useful for optimizing the matched filter to improve the successful rate of detection. In another reference by Opas Chutatape *et al.*[10] using tracking strategy for blood vessels detection in retinal fundus images, the Kalman filter is employed to estimate the next vessel segment location using not only the parameters of current segment but all previous vessel segments as well similar to tracking a flying object in the radar system. A Gaussian matched filter then locates the actual centerline midpoint based on the cross-section density profile at the estimated incremental section. The look-ahead distance and the searching window size are decided based on the error estimation of the Kalman filter. Instead of specifying points for the tracking to start by operators, the method uses the second order derivative of Gaussian filter to convolve with the density profile of a starting circle already detected such as optic disk where all vessels originate. The local maxima with high response are selected as the starting points of major vessels for the tracing algorithm to work. It seems the use Kalman filter posing a large amount of computation and the improvement in performance is not as obvious.

3. Classification of Blood Vessels

AWN classification method is used to the purpose of classify the clustered blood vessels with high accuracy. AWN classifies the input retinal image based on the features extracted and matches the features with the trained features. In our proposed method two level decision making is carried out because of the hybrid nature of our proposed classifier. In the initial level the concept of KNN classifier with hyper parameter of adaptive k size is implemented and classifies the nearest neighbours of the input image pixels. The clustered outputs are classified again using the concept of RF classifier by optimizing the number of trees which leads to high precision and accuracy in decision making. If the classifier verifies that the input retinal image is from the authorized user it provides an authentication and gives access to further processing.

In this algorithm two parameters expected to set up, first is the quantity of bunch K , the other is K' utilized amid every emphasis of k -closest neighbor. In this paper we pick arbitrary seed determination calculations since irregular is the straightforward. Generally it picks k focuses arbitrarily from the info set as the underlying focuses. The decision of K' directly harmed the execution of order, if the parameter is too little, you can't discover enough report to legitimately arrange, else it would be discover more neighbors in the far off bunches, so the record would be appointed wrongly to more removed groups. We adjust a dynamic K' change in every cycle, setting the closest neighbor parameter K' is the quantity of reports contained in the littlest class.

Algorithm for adaptive k' in AWN classifier:

Input: Training sample set TS , nearest neighbours W weights, the sample test set S

Output: Category c

Initialization: Select $c_1, c_2, \dots, c_k$ in C' as a group focus, each bunch is $C_1, C_2, \dots, C_w$
 Rehash
 For each remain c_i in C'
 Ascertain the similitude of c_i and $c_j, j=1, 2, \dots, k$
 On the off chance that $\text{Sim}(c_i, c_j) < \text{Sim}(c_i, c_n)$ at that point $C_n = C_n \cup \{c_i\}, n=1, 2, \dots, w$ adjust the bunch focus
 Until the point when every one of the pictures have their own particular bunch, which have an aggregate K groups
 For each test pictures utilizing the versatile weighted neighbor algorithm to group informational collections
 Repeat
 For every S Do Begin
 $W' = |\text{the bunch containing minimal weights of images}| + 1$
 For $W=1$ to W' TS0
 $TSt =$;in which TSt communicates the most comparable arrangement of pixels sets of test images
 For every c in C_i Do Begin
 On the off chance that T exist z_1 in C_j and z_2 in C_i making
 $\text{sim}(t, z_1) < \text{sim}(t, z_2)$ at that point
 Start
 $TSt = TSt - \{z_2\}$
 $TSt = TSt \cup \{z_2\}$
 End
 End if
 End
 Until the point when the class of the considerable number of pixels are never again changed;
 On the off chance that T and z_1 in TSt, z_2 in TSt and $|C_j| > |C_i|$ then C_j

End In the second step the least difficult random forest with random elements is framed by selecting at random, at every hub, a little gathering of information variables to part on. The steps are classified underneath:

To build K trees:

Building every tree by:

- Selecting, at random, at every hub a little arrangement of elements (F) to part on (given M highlights). Basic estimations of F are:
 - $F=1$.
 - $F=\log_2(M) + 1$.
- For every hub separate the best of this subset (utilizing oob occasions).
- Growing full length tree.

The proposed AWN calculation is a relationship between the adaptive k' and concept of random forest with optimized number of trees are prepared it called weighted neighbourhood plans.

These two models worked from a preparation sets $\{(x_i, y_i)\}_{i=1}^n$ that make predictions $\hat{y}$ for new points x' by viewed at the point of "neighbourhood", formalized by a weight function W ,

$$\hat{y} = \sum_{i=1}^n W(x_i, x') y_i$$

Here, $\{W(x_i, x')\}$ is the non-negative weight of the i 'th training point relative to the new point x' .

For any particular X' the weights must sum to one. Weight functions are given as follows:

In k-NN, $W(x_i, x') = \frac{1}{k}$ if ' x_i ' is one of the k points closest to x' , and zero otherwise.

In RF, $W(x_i, x') = \frac{1}{k'}$ if ' x_i ' is one of the k' points in the same leaf as x' , and zero otherwise.

Since a forest averages the predictions of a set of ' m ' trees with individual weight functions $W(j)$, its predictions are

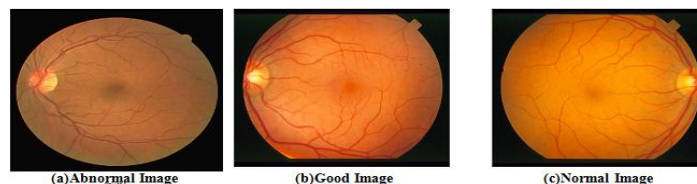
$$\hat{y} = \frac{1}{m} \sum_{j=1}^m \sum_{i=1}^n W(x_i, x') y_i$$

$$\hat{y} = \sum_{i=1}^n \frac{1}{m} \left(\sum_{j=1}^m W(x_i, x') y_i \right)$$

The neighbours of x' in this interpretation are the points $x(i)$ which fall in the same leaf as x' in at least one tree of the forest. In this way, the neighbourhood of x' depends in a complex way on the structure of the training set.

4. Experimental Results

The above results shows the comparison of abnormal, good and normal images and their proposed AWN classifier outputs and Adam hoover's outputs for the DRIVE database.



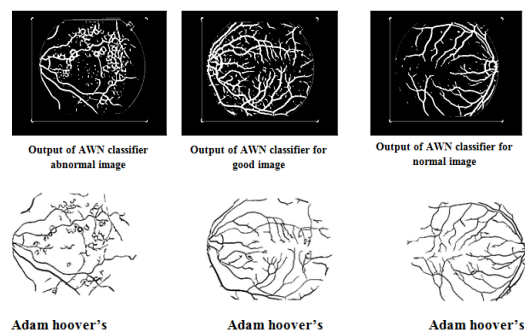


Fig. 1: Outputs of Drive Database

The below results is for the STARE database

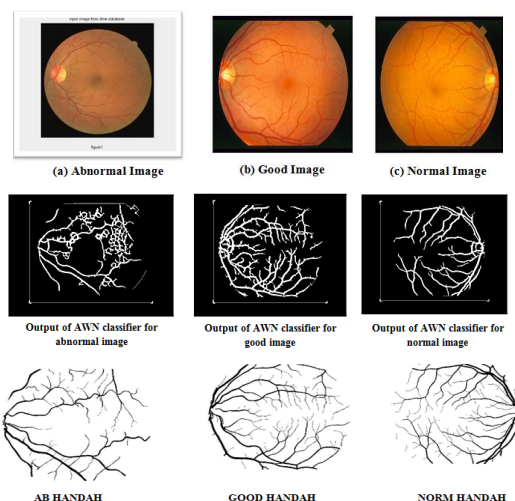


Fig. 2: Outputs of Stare Database

Table I: Comparison of Hoover and Proposed Method

Segmentation Method	Stare Accuracy	Drive Accuracy
Our Method	0.9485	0.9437
Hoover	0.9275	0.9225

5. Conclusion

The Automatic analysis of blood vessels in the retinal images can help physicians for the purpose of diagnosing ocular diseases, patient screening and clinical study, etc. Human retina is a source of biometric system which provides the most reliable and stable means of authentication. As the structure of retinal blood vessel is unique it plays an important role in retinal biometrics. The proposed algorithm takes in to account the advantages of the intensity information of from green channels of the same retinal image and AWN Classifier. AWN Classifier, which takes in to account the spatial distribution of gray levels, performs efficiently in distinguishing between enhanced vessel

segments and background since it can preserve the structure details of an image. In this paper we describe a new approach to automatically detect blood vessels in retinal images. We tested our methods on a set of 20 ocular fundus images and experimental results are compared with those obtained from state of the art method and hand labeled ground truth segmentations. The accuracy achieved by our method are 0.9485 for DRIVE database and 0.9437 for STARE database.

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