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DETECTING AND SEGMENTING DIGITAL RETINAL BLOOD VESSELS USING NEURAL NETWORK

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Abstract: **This paper introduced a supervised method for blood vessel detection in digital color retinal images. Neural network (NN) scheme is used for pixel classification and computes a 7-D vector composed of gray-level and moment invariants-based features for pixel representation. DRIVE databases are used for this purpose. Segmentation of blood vessels in retinal images allows early diagnosis of diseases. The results are encouraging and will be used for further application such as personal identification and are evaluated in terms of sensitivity and specificity and accuracy.**

Keywords: **Diabetic retinopathy, moment invariants, retinal blood vessel segmentation, gray level features.**

I. INTRODUCTION

DIABETIC retinopathy (DR) is the leading ophthalmic pathological cause of blindness among people of working age in developed countries [1]. People affected by diabetic are more facing eye problems like contracts and glaucoma and the main reason for vision loss is the disease affecting on retina. The complications of diabetes affect the vascular structure of human retina and cause the leakage of blood on surface of retina which leads to blindness and it is known as diabetic retinopathy[2],[3].

Diabetic retinopathy is a progressive disease as there are no such signs of disease at its early stages but as the time passes the disease turns into severe. The common symptoms of diabetic retinopathy are blurred vision and even loss of vision if not treated in time.[3] The main cause of DR is abnormal blood glucose level elevation, which damages vessel endothelium, thus increasing vessel permeability.

Diabetic retinopathy is primarily classified into non proliferative DR (NPDR), formerly termed simple, or background retinopathy, and proliferative DR (PDR). Progression from mild, characterized by increased vascular permeability, to moderate, and then to severe NPDR characterized by vascular closure and an increased risk for the development of PDR distinguished by the growth of new blood vessels on the retina and posterior surface of the vitreous[3].

The first manifestations of DR are tiny capillary dilations known as micro aneurysms. DR progression also causes neovascularization, hemorrhages, macular edema and, in later stages, retinal detachment. In this paper, a new methodology for blood vessel detection is presented.

It is based on pixel classification using a 7-D feature vector extracted from preprocessed retinal images and given as input to a neural network.

Classification results (real values between 0 and 1) are threshold to classify each pixel into two classes: vessel and non vessel. Finally, a post processing fills pixel gaps in detected blood vessels and removes falsely-detected isolated vessel pixels[4].

The eye fundus photographs present inadequate contrast, lighting variations, noise influence and anatomic variability affecting both the retinal background texture and the blood vessels structure. Blood vessels particular features make them complex structures to detect as the color of vascular structures is not constant even along the same vessel.[5] Their complex tree-like geometry includes bifurcations and overlaps that may mix up the detection system. As blood vessels segmentation becomes essential for several medical diagnostic systems, numerous research efforts have been done in this field.

Many approaches for extracting retinal image vessels have been developed and applied. The matched filter approach is a widely used template-based method, which was firstly proposed by Chaudhuri and further extended by Hoover. This method usually uses a two-dimensional linear structural element that has a Gaussian cross-profile section, extruded or rotated into three dimensions to identify the cross profile of the blood vessels. However, with this method in the detected images, the junction points are not always detected small vessels are missed and the validity of the detected vessels is not checked.

There are three basic approaches for automated segmentation of blood vessel: thresholding method, tracking method and machine trained classifiers. In the first method, many of different operators are used to enhance the contrast between vessel and background, such as Sobel operators, Laplacian operators, Gaussian filters which model the gray cross-section of a blood vessel. Then the gray threshold is selected to determine the vessel. And this gray threshold is crucial, because small threshold induces more noises and great threshold causes loss of some fine vessels, so adaptive or local threshold is used to different sections of an image.

This method is to segment retinal blood vessels to overcome the variations in contrast of large and thin vessels. This method uses adaptive local thresholding to produce a binary image then extract large connected components as large vessels.[8] The residual fragments in the binary image including some thin vessel segments (or pixels), are classified by Support Vector Machine(SVM). The tracking growth is applied to the thin vessel segments to form the whole vascular network. It distinguishes large vessels by adaptive local thresholding for their good contrast.[7] Then identify some thin vessel segments with bad contrast by SVM, which can be lengthened by tracking. This method can avoid heavy computation and manual intervention.

The binary images of manual segmentation and the masks of field of view (FOV) are available for all the images of the two sets. All the images were manually segmented. In order to ensure accurate classification for most noise pixels the SVM is used continually until the number of remained pixel is less than 1000. According to the training set, there are about 1500 thin vessel pixels and more than 10000 non-vessel pixels in each residual image.

However, relatively low accuracy is a shortage, which is due to the inflated width of large vessels in image preprocessing. The rest of the paper is ordered as follows. Following section analyses further issued vessel segmentation solutions. Section III designates the material used in this study. Section IV presents its experimental results and links them to those obtained with other existing methods while Section V describes the conclusions and discussion of this paper.

II. STATE OF ART

Blood vessel separation can be completed in several methods. The matched filtering is to boost the blood vessels. Entropy-based thresholding can well retain the spatial structure of vascular tree segments. Length filtering is used to remove misclassified pixels. The algorithm has been tried on twenty ocular fundus images, and experimental results are compared with those obtained from a state-of-the-art method and hand-labeled ground truth segmentations.

The gray-level profile of the cross section of a blood vessel can be approximated by a Gaussian shaped curve. The concept of matched filter detection is used to detect piecewise linear segments of blood vessels in retinal images. Blood vessels usually have poor local contrast. The two-dimensional matched filter kernel is designed to convolve with the original image in order to enhance the blood vessels [6].

To improve the robustness of our algorithm by involving color information and additional anatomical constraints for blood vessel detection and extraction. An efficient algorithm is used for fully automated blood vessel detection in ocular fundus images using the local entropy Thresholding scheme [7]-[9]. The proposed method retains the computational simplicity, and at the same time, can achieve accurate segmentation results in the case of normal retinal images and images with obscure blood vessel appearance.

In the case of abnormal retinal images with lessons, some lesions are also misdetected in addition to blood vessels. In the future work, we want to improve the robustness of our algorithm by involving in the preprocessing scheme and additional anatomical constraints to isolate the lesions in the final vascular tree [7]. A Bayesian classifier is created on the idea that the role of a (natural) class is to predict the values of features for members of that class. Examples are grouped in classes because they have common values for the features. Such classes are often called natural kinds. In this section, the target feature resembles to a discrete class, which is not certainly binary [10].

Supervised methods are grounded on pixel classification, which comprises on classifying each pixel into two classes, vessel and non-vessel. Classifiers are trained by supervised learning with data from manually-labeled images. Gardner proposed a back propagation multilayer neural network (NN) for vascular tree segmentation. After histogram equalization, smoothing and edge detection, the image was separated into 20x20 pixel squares (400 input neurons).

The NN was then fed with the values of these pixel windows for classifying each pixel into vessel or not. Sinthanayothin also used a multilayer perceptron NN. Each pixel in the image was classified by using the first principal module, and the edge strength values from a 10x10 pixel sub image aligned on the pixel under estimation, as input data. Niemeijer executed a K-nearest neighbor (KNN) classifier.[13]

III. OFFERED SCHEME

Artificial neural network is a system closely modeled on the human brain. Artificial neural network contains the multiple layers of simple processing elements called neuron. Each neuron is linked to certain of its neighbors with coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths to cause the overall network to output appropriate results.

Diagnostic systems, biochemical analysis, image analysis and drug development are the various areas in medicine where artificial neural network is used successfully. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information.

The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. A neuron is a nerve cell that is the basic building block of the nervous system. Neurons are similar to other cells in the human body in a number of ways, but there is one key difference between neurons and other cells.

Neurons are specialized to transmit information throughout the body. Sensory neurons carry information from the sensory receptor cells throughout the body to the brain. Motor neurons transmit information from the brain to the muscles of the body. Interneurons are responsible for communicating information between different neurons in the body.

This paper suggests a new supervised attitude for blood vessel detection founded on a NN for pixel classification. Input images (fig 2.a)are engaged as the color fundus image which is read from the DRIVE database. Amongst the RGB demonstration, green channel is mined. The required feature vector is figured from preprocessed retinal images in the neighborhood of the pixel under consideration.

The following process points may be known: 1) Original fundus image preprocessing for gray-level homogenization and blood vessel enhancement, 2) feature extraction for pixel numerical representation, 3) Application of a classifier to label the pixel as vessel or non-vessel, and 4) Post processing for filling pixel gaps in detected blood vessels and removing falsely-detected isolated vessel pixels.[8]-[11]

A Neuro fuzzy classifier is an algorithm which is used for sensing the blood vessel with better accuracy than further algorithm. The classifier assigns a class label to an object, based on the object description. It is also said that the classifier predicts the class label. The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task. Typically, the classifier learns to predict class labels using a training algorithm and a training data set.

When a training data set is not available, a classifier can be designed from prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach.

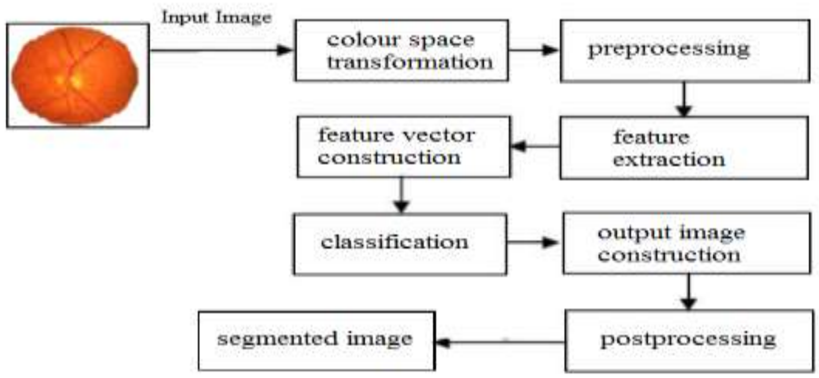

Fig.1 simplified block diagram

A. Preprocessing

In order to decrease the deficiencies similar to lighting variations, poor contrast and noise, preprocessing is done. It comprising the following steps 1) vessel central light reflex removal, 2) background homogenization, and 3) vessel enhancement.

1) Vessel Central Light Reflex Removal

Subsequently retinal bloodvessels have lower reflectance when equated to other retinal surfaces, they seem darker than the background. Though the typical vessel cross-sectional gray-level profile can be approached by a Gaussian shaped curve, some blood vessels embrace a light streak which runs down the central length of the blood vessel

. The green plane of the image (fig 2.b) is filtered by applying a morphological opening using a three-pixel diameter disc to remove this brighter strip, described in a square grid by using eight-connexity, by way of structuring element. Disc diameter was secured to the possible minimum value to shrink the threat of merging close vessels.

Fig 2. (a) Input image

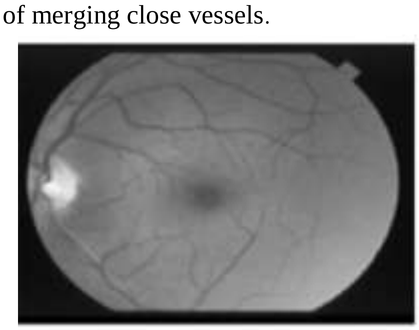

Fig 2. (b) Green channel

2) Background Homogenization

Fundus images frequently comprise background intensity variation due to nonuniform radiance. Accordingly, background pixels may have dissimilar intensity for the same image and, although their gray-levels are generally greater than those of vessel pixels, the concentration values of some background pixels is analogous to that of brighter vessel pixels.

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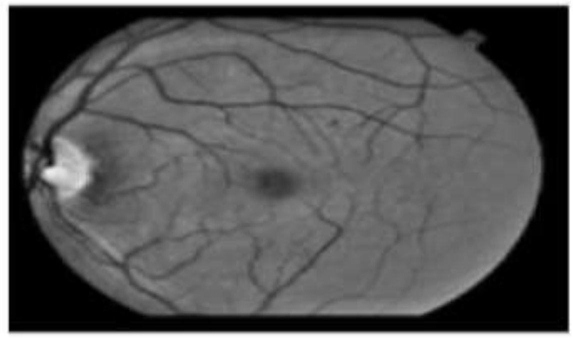

Fig. 3) homogenized image

Subsequently the feature vector used to characterize a pixel in the classification stage is formed by gray-scale values, this result may degrade the presentation of the vessel segmentation procedure. With the resolution of removing these background lightening variations, a shade-corrected image is skilled from a background estimate. This image is the outcome of a filtering operation with a large arithmetic mean kernel, as described

Firstly, a 3 x 3 mean filter is applied to smooth occasional salt-and-pepper noise. Additional noise smoothing is achieved by convolving the subsequent image with a Gaussian kernel of dimensions m x m= 9 x 9. Furthermore, a background image, IB is formed by applying a 69 x 69 mean filter. The difference D between IG and IB is calculated as,

$$D(x,y)=IG(x,y)-IB(x,y) \quad (1)$$

Moreover the background intensity variations in images, intensities can expose significant variations amongst images due to altered illumination conditions in the acquisition process. In order to decrease this effect, a homogenized image (fig 3) IH is created as,

$$IH=ISC+128-\max(ISC) \quad (2)$$

3) Vessel Enhancement

The final preprocessing step entails on producing a fresh vessel-enhanced image IVE, which verifies more proper for further removal of moment invariants- based features. Vessel enhancement is achieved by approximating the complementary image of the homogenized image, and then applying the morphological Top-Hat transformation.

Although bright retinal structures are isolated (i.e., optic disc, possible presence of exudates or reflection artifacts), the darker structures lasting after the opening operation become boosted (i.e., blood vessels, fovea, probableoccurrence of micro aneurysms or hemorrhages).

B.Feature Extraction

Feature extraction is a superior form of dimensionality reduction. While the input data to an algorithm is too large to be processed and it is assumed to be notoriously redundant then the input data will be transmuted into a reduced illustration set of features.

The goal of the feature extraction stage is pixel characterization by means of a feature vector, a pixel representation in terms of some quantifiable measurements which may be simply used in the classification stage to resolve whether pixels belong to a real blood vessel or not. In this paper, the following sets of features were designated.

1) Gray-level-based features

Gray level fratures are the statistical information about the image like energy, correlation etc. Features established on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings.

Since blood vessels are constantly darker than their surroundings, features based on describing gray-level variation in the surroundings of candidate pixels appear a noble choice.

A set of gray-level-based descriptors taking this material into account were derived from homogenized images IH considering only a small pixel region positioned on the described pixel (x,y). S^wx,y views for the set of coordinates in a *wxw* sized square window centered on point (x,y). Then, these descriptors can be expressed as

$$f1(x,y)=IH(x,y)- \min\{IH(s,t)\} \quad (3)$$

$$f2(x,y)=max\{IH(s,t)\} - IH(x,y) \quad (4)$$

$$f3(x,y)= IH(x,y)- mean\{IH(s,t)\} \quad (5)$$

$$f4(x,y)= std\{IH(s,t)\} \quad (6)$$

$$f5(x,y)=IH(x,y) \quad (7)$$

2) Moment invariants-based features

Features based on moment invariants for relating small image regions made by the gray-scale standards of a window centered on the represented pixels. The vasculature in retinal images is identified to be piecewise linear and can be approached by many connected line sections. For perceiving these quasi-linear shapes, which are not all similarly wide and may be sloping at any angle, shape descriptors invariant to translation, rotation and scale change may play an vital role.

C. Classification

In the feature extraction stage, individual pixel from a fundus image is considered by a vector in a 7-D feature space

$$F(x, y) = (f1(x, y) \ldots f7(x, y)) \quad (8)$$

Currently, a classification procedure assigns one of the classes C1 (vessel) or C2 (nonvessel) to each candidate pixel when its representation is known. In order to prefer a proper classifier, the dispersal of the training set data in the feature space was studied. The outcomes of this enquiry showed that the class linear separability grade was not high sufficient for the accuracy level vital for vasculature segmentation in retinal images.

In this multilayer feed forward network, the signal flows from the input unit to the output unit in a forward direction. The multilayer pose one or more layers of node between the input and output units. This is useful over single layer net in the sense that, it can be used to solve more complicated problems.

The bright pixels in this image indicate higher probability of being vessel pixel. In order to get a vessel binary segmentation, a thresholding structure on the probability map is used to decide whether a particular pixel is part of a vessel or not. Therefore, the classification procedure allots one of the classes C1 or C2 to each candidate pixel, depending on if its associated probability is greater than a threshold.

Some misclassified pixels looked as undesirable noise in the classified image. Moreover, for some vessels, only their boundaries were ordered, so that it was needed to do post processing by using morphological tools to obtain the final desired segmentation. Finally, to optimize the vessel contours, morphological operations have been applied, beginning by area open to eliminate small noisy components. The final vessel segmented image after postprocessing is formed as shown in fig 4.

Fig. 4) Final segmented image

1) *ANFIS Classifier*

Adaptive neuro fuzzy inference system (ANFIS) is a kind of neural network that is based on Takagi–Sugeno fuzzy inference system. Since it integrates both neural networks and fuzzy logicprinciples, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions.[1] Hence, ANFIS is considered to be a universal estimator.

2) *Neuro fuzzy classifer*

In the field of artificial intelligence, neuro-fuzzy states to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks.

Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System in the literature. Neuro-fuzzy system joins the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules.

IV. EXPERIMENTS

From the observation the following parameter values are determined,

Method	Specificity	Sensitivity
MLP	56.42	21.11
FUZZY	60.42	25
ANFIS	60.42	25

Method	accuracy	NPV	PPV
MLP	74.3	76.6	9.56
FUZZY	83.69	99.75	0.123
ANFIS	93.41	99.75	0.123

The method is verified with all the 20 images in the DRIVE database. There are two manual segmented image sets available in the database. These manual segmented image is matched with the planned result and the final segmented image equals more with the manual segmented image.

V. DISCUSSION AND CONCLUSION

Proposed vessel extraction method does not involve any user intervention, and has reliable performance in both normal and abnormal images. Higher accuracy than that of other previously can be stated vessel segmentation methods. The results proved herein specifies that automated identification of retinal blood vessels based on NN classifiers can be very popular.

Therefore, eye care specialists can possibly display larger populations by means of this method. Furthermore, remarks based on such a device would be steadily reproducible. To catch out a vessel pixel, fine classified training set is essential, since machine learning needs enough samples to arrest the simple structure so that it can be generalized to new cases .Studies may familiar with Multilayer feed forward, fuzzy, anfis neural network, the accuracy can be improved further turning of the network. Consuming proposed method, image with fluctuating sizes can be verified.

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