Segmentation of Blood Vessels in Retinal Images Based on Neural Network (Nn) Scheme of Gray-Level and Moment Invariants-Based Features

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Abstract

In this paper presents , segmentation of blood vessels in retinal images based on neural network (NN) scheme of gray-level and moment invariants-based features. In the past, rural based methods are used segment the blood vessels. It has more complexity and less accuracy of blood vessels detection in retinal images. This paper proves better performance in terms of blood vessel detection in stare and retinal images. Its effectiveness and robustness with different image conditions, together with its simplicity and fast implementation, make this blood vessel segmentation proposal suitable for retinal image computer analyses such as automated screening for early diabetic retinopathy detection. The simulation results shows the better blood vessels detections in retinal images

Index term

Diabetic retinopathy, moment invariants, retinal imaging, telemedicine, vessels segmentation

I. INTRODUCTION

Vessel Segmentation is an important task in medical imaging and has been investigated extensively in the past. Diabetic retinopathy is the leading cause of blindness among adults aged 20-74 years in the United States [1] and is estimated to affect 28.5% of US adults with diabetes [2]. According to the World Health Organization (WHO), screening for diabetic retinopathy is essential for diabetic patients and will reduce the burden of disease [3]. Other diseases affecting the retina can also be detected by a regular direct visual examination.

Coronary angiography is a medical examination that uses X-Ray imaging to find stenoses in coronary arteries. To locate such an abnormal narrowing of a vessel a catheter is put into an artery in the groin or arm and guided to the heart. A contrast agent is injected several times to visualize the vessel and aid navigation of the catheter, guidewire, balloon and stent in the coronary tree. Segmentation is performed during the short period in which the vessel is visible in order to use this information later in the procedure and for future analysis. There is a plethora of different segmentation methods for vessels. Some are specific to different kinds of vessels, such as retina vessels or different modalities such as CT or MRI. Only few papers handle the case of angiographic videos. [4] provides an extensive overview of different methods putting them in categories such as (i) pattern recognition, (ii) model based, (iii) tracking based and (iv) artificial intelligence.

Few papers exist that use machine learning techniques. [5] uses wavelet features and k-Nearest Neighbor to label pixels as inside or outside of a vessel. A similar approach that also uses k-Nearest Neighbor ([6]) is one of the few papers to present quantitative results. However, its results are im-practical for our purpose, since the method needs about 15 minutes to segment one image of a retina vessel and are not robust against edges that are not vessels. In angiography, such edges frequently occur in form of background organs.

II. PROPOSED METHOD

This paper proposes a new supervised approach for blood vessel detection based on NN pixel classifications. The necessary feature vector is computed from preprocessing retinal images in the neighborhood of pixels under considerations.

The block diagram of gray-level and moment invariants-based features based on NN as shown below.

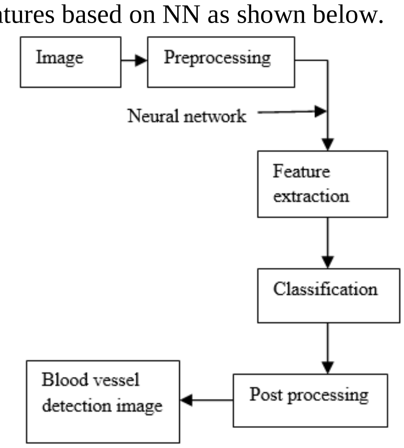

Fig.1. block diagram of proposed method

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a) Preprocessing

It is calculate the feature vector of retinal images in the neighborhood of pixels. To reduce the imperfection and extract the pixel feature vectors using following steps.

i) Vessel Central Light Reflex Removal:

To remove the vessel central light using morphological operations. In this paper use sobel operators along horizontal and vertical directions, a large vessel always corresponds to a pair of local gradient maximum and minimum on both sides along a profile. And the edge of the opticdisk corresponds to a single local maximum or minimum.

ii) Background Homogenization:

In retinal images, different lighr condition are occur in background pixel. So, to remove the background lightening variations, a shade-corrected image is accomplished from a background estimate. This image is the result of a filtering operation with a large arithmetic mean kernel. firstly, a3x 3 mean filter is applied to smooth occasional salt-and-pepper noise. further noise smoothing is performed by convolving the resultant image with a gaussian kernel of dimensions, mean and variance. secondly, a background image , is produced by applying a6x 6 mean filter. finally, a shade-corrected image is obtained by transforming linearly values into integers covering the whole range of possible gray-levels (0 –255 , referred to 8- bit images).

iii) Vessel Enhancement:

The final preprocessing step consists on generating a new vessel-enhanced image, which proves more suitable for further extraction of moment invariants- based features. While bright retinal structures are removed(i.e., optic disc, possible presence of exudates or reflection artifacts, the darker structures remaining after the opening operation become enhanced (i.e., blood vessels, fovea, possible presence of micro aneurysms or hemorrhages).

B.Feature Extraction

Feature extraction is a special form of dimensionality reduction. Then the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information then the input data will be transformed into a reduced representation set of features. The aim of the feature extraction stage is pixel characterization by means of a feature vector, a pixel representation. In this paper, the following sets of features were selected.

C.Classification

In the feature extraction stage, each pixel from a fundus image is characterized by a vector in a 7-Dfeature space supervised classification has been applied to obtain the final segmentation, with the pixel classes defined as
C1 = {vessel pixels} and C2 = {non-vessel pixels}.
In order to obtain the training set, several fundus image h ave been manuallysegmented, allowing the creation of a labeled training set into classes C1 and C2.Due to the computational cost of training the classifiers and the large number of samples, we randomly select a subset of the available samples to use for actually raining the classifier.
Two classification stages can be distinguished: a design stage, in which the NNconfiguration is decided and the NN is trained, and an application stage, in which the trained NN is used to classify each pixel as vessel or non vessel to obtain a vessel binary image.

i) Neural Network Design:

A multilayer feed forward network, consisting of an input layer, three hidden layers and an output layer, is adopted in this paper. The input layer is composed by a number of neurons equal to the dimension of the feature vector (seven neurons). Degrading the hidden layers, several topologies with different numbers of neurons were tested. A number of three hidden layers, each containing 15 neurons, provided optimal NN configuration. The output layer contains a single neuron and is attached.

ii) Neural Network Application

At this stage, the trained NN is applied to an “un seen” fundus image to generate a binary image in which blood vessels are identified from retinal background: pixels’ mathematical descriptions are individually passed through the NN.

D. Post processing

Classifier performance is enhanced by the inclusion of a two step post processing stage: the first step is aimed at filling pixel gaps in detected blood vessels, while the second step is aimed at removing falsely detected isolated vessel pixels. The output produced by the classifier leads to a binary image where each pixel is labeled as vessel or non-vessel. Some misclassified pixels appeared as undesirable noise in the classified image. In addition, for some vessels, only their boundaries were classified, so that it was necessary to perform 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.

III. EXPERIMENTAL RESULTS

the classification analysis indicated that the best optimum classifier for distinguishing vascular pixels is a NN classifier with 10 hidden units. Typical abnormal retinal image from the image dataset that has been classified at pixel level using the optimum NN classifier and various processes. The majority of large and small vessels were detected; there was erroneous detection of noise and other artifacts. The overall segmentation process is illustrated through figure 5 and 6.The majority of errors were due to background noise and non-uniform illumination across the retinal images, the border of the optic disc. Those noises could easily be overcome through four processing stages.

Fig.2. green channel input image.

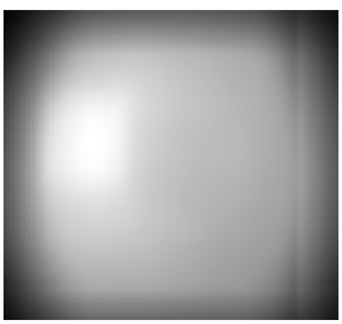

Fig.3. background image

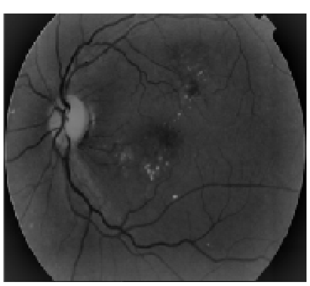

Fig.4. shade corrected image

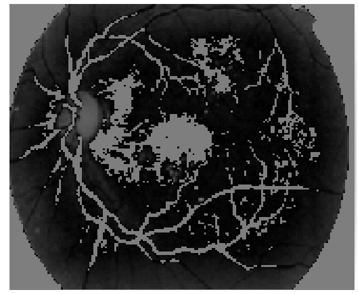

Fig.5. homogenized image

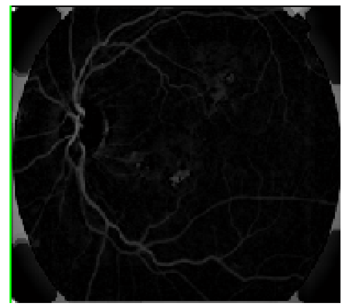

Fig6. Vessels enhanced image

Fig.7. vessel detection using proposed method

IV. CONCLUSION

In this paper propose the vessel extraction technique does not require any user intervention, and has consistent performance in both normal and abnormal images. Ligher accuracy than that of other previously can be reported vessel segmentation methods. The results demonstrated here in indicate that automated identification of retinal blood vessels based on Gabor filter responses and NN classifiers can be very successful. Hence, eye care specialists can potentially monitor larger populations using this met hod. furthermore, observations based on such a tool would be systematically reproducible

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