

Blood Vessel Segmentation for Retinal Images Based on Am-fm Method

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Abstract: This system proposes a new supervised approach for the blood vessel segmentation method in retina image. This proposed system overcomes the problem of segmenting thin vessels. This method uses a Fuzzy Neural Network (FNN) scheme for pixel classification and computes a 7-D vector composed of gray-level, moment invariants-based features for pixel representation and AM-FM method for composition of the images. The method was evaluated on the publicly available DRIVE and STARE databases, widely used for this purpose, since they contain retinal images where the vascular structure has been precisely marked by experts. Method performance on both sets of test images is better than other existing solutions in literature. The method proves especially accurate for vessel detection in STARE 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.

Keywords: Diabetic retinopathy, moment invariants, retinal imaging, vessels segmentation

INTRODUCTION

Diabetic Retinopathy (DR) is the leading ophthalmic pathological cause of blindness among people of working age in developed countries (Anonymous, 2005). It is provoked by diabetes-mellitus complications and, although diabetes affection does not necessarily involve vision impairment, about 2% of the patients affected by this disorder are blind and 10% undergo vision degradation after 15 years of diabetes (Carla, 2010; Author, 2008) as a consequence of DR complications. The estimated prevalence of diabetes for all age groups worldwide was 2.8% in 2000 and 4.4% in 2030, meaning that the total number of diabetes patients is forecasted to rise from 171 million in 2000 to 366 million in 2030 (Fong *et al.*, 2003). The main cause of DR is abnormal blood glucose level elevation, which damages vessel endothelium, thus increasing vessel permeability. The first manifestations of DR are tiny capillary dilations known as microaneurysms. Although DR is not a curable disease, laser photocoagulation can prevent major vision loss if detected in early stages (Anonymous, 2005; Klein *et al.*, 1995).

However, DR patients perceive no symptoms until visual loss develops, usually in the later disease stages, when the treatment is less effective. So, to ensure the treatment is received in time, diabetic patients need annual eye-fundus examination (Lee *et al.*, 1991).

Knowledge on blood vessel location can be used to reduce the number of false positives in microaneurysm and hemorrhage detection (Taylor and Keeffe, 2001). In this study, a new methodology for blood vessel detection is presented. It is based on pixel classification using a 7-D feature vector extracted from pre-processed 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. Post-processing fills pixel gaps in detected blood vessels and removes falsely-detected isolated vessel pixels.

LITERATURE REVIEW

In this section, we summarize the basic algorithms proposed in the literature.

In the Fuzzy Vessel Tracking Algorithm, present a new unsupervised fuzzy algorithm for vessel tracking that is applied to the detection of the ocular fundus vessels. The proposed method overcomes the problems of initialization and vessel profile modelling that are encountered in the literature and automatically tracks fundus vessels using linguistic descriptions like "vessel" and "non vessel." The main tool for determining vessel and non vessel regions along a vessel profile is the fuzzy C-means clustering algorithm that is fed with properly pre-processed data.

In the Retinal blood vessel segmentation using Line operators and Support Vector Classification, retinal vessel segmentation based on line operators is proposed. A line detector is applied to the green channel of the retinal image. It is based on the evaluation of the average grey level along lines of fixed length passing through the target pixel at different orientations. Two segmentation Methods are considered. The first uses the basic line detector whose response is threshold to obtain unsupervised pixel classification. As a further development, we employ two orthogonal line detectors along with the grey level of the target pixel to construct a feature vector for supervised classification using a support vector machine.

In the segmentation of Retinal Blood Vessels by Combining the Detection of Centrelines and Morphological Reconstruction, This method produces segmentations by classifying each image pixel as *vessel* or *non vessel*, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. The Gabor wavelet is capable of tuning to specific frequencies, thus allowing noise filtering and vessel enhancement in a single step. We use a Bayesian classifier with class-conditional probability density functions described as Gaussian mixtures, yielding a fast classification, while being able to model complex decision surfaces. The probability distributions are estimated based on a training set of labelled pixels obtained from manual segmentations.

METHODOLOGY

Proposed vessel segmentation:

Method: This study proposes a new supervised approach for blood vessel detection based on a NN for pixel classification. Input images are monochrome and obtained by extracting the green band from original RGB retinal images. The green channel provides the best vessel-background contrast of the RGB representation and provides the following steps.

Pre-processing: Color fundus images often show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a pre-processing comprising the following steps is applied:

- **Vessel central light reflex removal:** Since retinal blood vessels have lower reflectance when compared to other retinal surfaces, they appear darker than the background. To remove this brighter strip, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter

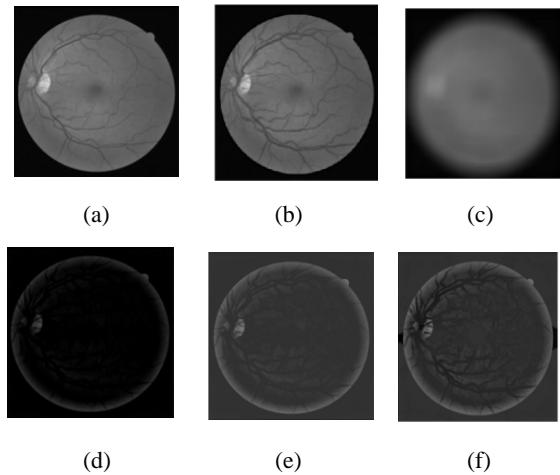


Fig. 1: Illustration of the pre processing process., (a) Green channel of the original image. (b) The vessel central light reflex removal, (c) The background image, (d) Shade-corrected image, (e) Homogenized image, (f) Vessel enhanced

disc, defined in a square grid by using eight-convexity, as structuring element. Figure 1 shows the way of the various pre-processing process represented by AM-FM.

- **Background homogenization:** Fundus images often contain background intensity variation due to non uniform illumination. Firstly, a 3X3 mean filter is applied to smooth occasional salt-and-pepper noise. Secondly, a background image I_B , is produced by applying a 69X69 mean filter. Finally, the shade-correction algorithm is observed to reduce background intensity variations and enhance contrast in relation to the original green channel image.
- **Vessel enhancement:** The final pre processing step consists on generating a new vessel enhanced image (I_{VE}) which proves more suitable for further extraction of moment invariants based features. Vessel enhancement is performed by estimating the complementary image of the homogenized image I_H , I^c_H and subsequently applying the morphological *Top-Hat transformation*:

$$I_{VE} = I^c_H - \gamma(I^c_H)$$

where, γ is a morphological opening operation using a disc of eight pixels in radius. Figure 2 Shows the complementary homogenized image and the transformation of Morphological and Vessel Enhanced Image.

Feature extraction: In this study, the following sets of features were selected.

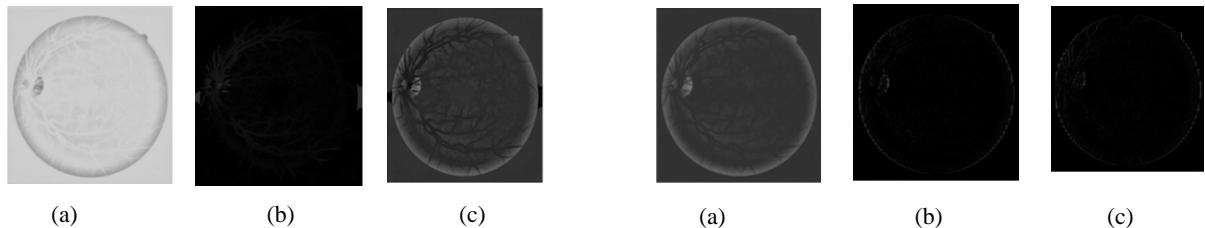


Fig. 2: (a) The complementary homogenized image, (b) Apply the morphological top-hat transformation, (c) The vessel enhanced image

- **Gray-level-based features:** Features based on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings.
- **Moment invariants-based features:** Features based on moment invariants for describing small image regions formed by the gray-scale values of a window centered on the represented pixels.

Classification: A classification procedure assigns one of the classes C1 (vessel) or C2 (non vessel) to each candidate pixel when its representation is known. Two classification stages can be distinguished: a design stage, in which the NN configuration 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.

Neural network design: A multilayer feed forward network, consisting of an input layer, three hidden layers and an output layer, is adopted in this study.

Neural network application: At this stage, the trained NN is applied to an “unseen” fundus image to generate a binary image in which blood vessels are identified from retinal background. In our case, the NN input units receive the set of features provided by Gray-level-based features, moment invariants-based features and AM-FM texture features. Figure 3 Shows the Homogenized image and Gray-level based feature is represented by AM-FM method.

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.

From visual inspection of the NN output, vessels may have a few gaps. To overcome this problem, an iterative filling operation is performed by considering that pixels with at least six neighbours classified as vessel points must also be vessel pixels. In order to remove these

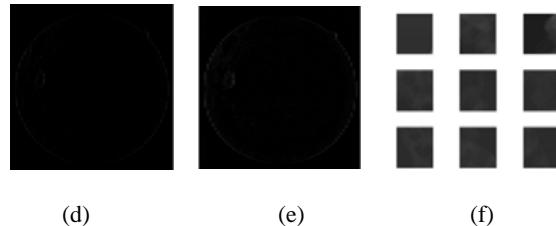


Fig. 3: (a) Homogenized image, (b)-(f) Gray-level based features

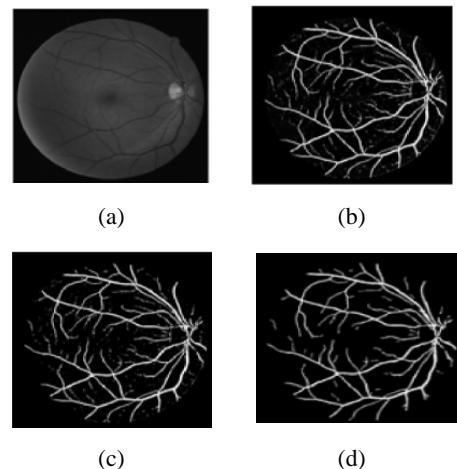


Fig. 4: (a) Green channel of the original image, (b) Obtained probability map represented as an image, (c) Threshold image, (d) Post-processed image

artifacts, the pixel area in each connected region is measured. Figure 4 Shows the Post-processing of Green channel of the original image and it's represented by the portability map, Threshold and post-processed image. In artifact removal, each region connected to an area below 25 is reclassified as non vessel.

Blood vessel segmentation based on AM-FM approach: In this study, our algorithm uses a technique called Amplitude Modulation-Frequency Modulation (AM-FM) to define the features and to characterize normal and pathological structures based on their pixel intensity, size and geometry at different spatial and spectral scales. In order to extract information from an image, this technique decomposes the green channel of the images into different representations which reflect the

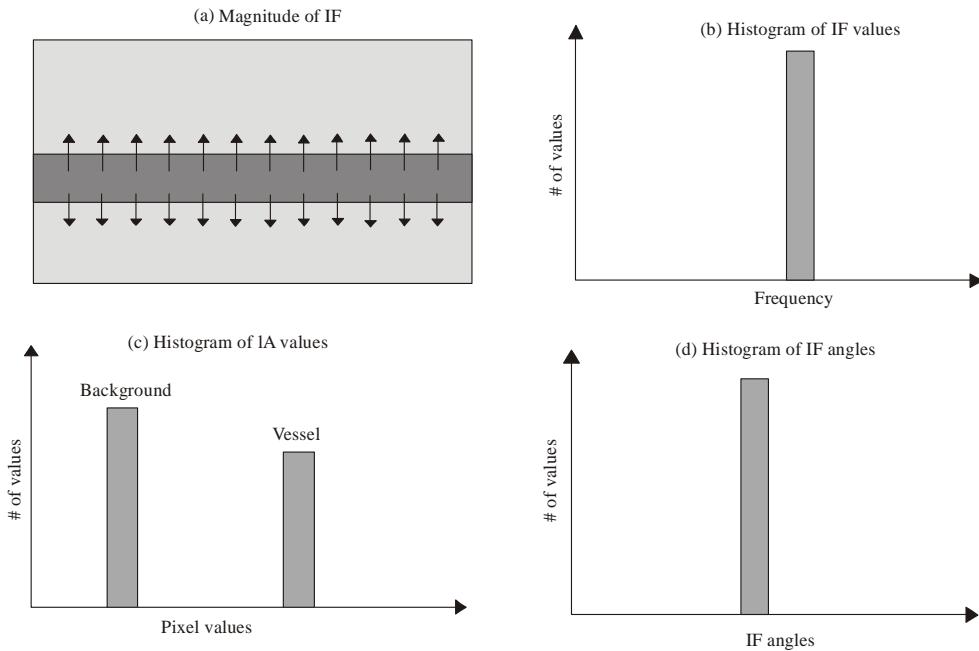


Fig. 5: Conceptual AM-FM analysis for horizontally-oriented blood vessel edge, (a) Instantaneous frequencies on top of vessel-like structure, (b) Instantaneous frequency histogram, (c) Instantaneous amplitude histogram, (d) IF angle histogram

intensity, geometry and texture of the structures in the image. The AM-FM decomposition for an image is given by: where M is the number of AM-FM components denotes Instantaneous Amplitude estimate (IA) and denotes instantaneous phase. Using the latter, two AM-FM estimates are generated by extracting the magnitude and the angle of its gradient. These estimates are called Instantaneous Frequency magnitude ($|IF|$) and instantaneous frequency angle.

In addition to obtaining this information per image, filters are applied to obtain image representations in different bands of frequencies. For example, if a medium or high pass filter is applied to an image, the smaller retinal structures (e.g., MAs, dot-blot hemorrhages, exudates etc.) are enhanced. Using these two ways of processing (AM-FM image representations and output of the filters), more robust signatures of the different pathologies can be characterized. At the end of this step, an image has 39 different representations that characterize the different pathologies found in the retina. AM-FM represents two structures commonly found in DR images: retinal vessels and rounded dark lesions. The same analysis to be presented here can be done for bright lesions, large hemorrhages and abnormal vessels, among other retinal features.

Figure 5 shows the way a horizontally oriented retinal vessel is represented by AM-FM and the resulting histograms for the three different AM-FM estimates: Instantaneous Amplitude (IA), Instantaneous Frequency

magnitude ($|IF|$) and instantaneous frequency angle. The arrows in Fig. 5a show the direction in which the frequency change is happening, meaning, the way the pixel values are changing from dark (vessel) to bright (retinal background). The pixels in the background will only have slight changes in intensity and therefore their frequencies are close to zero. The only areas generating a frequency response are those in the edge of the vessels and they will have a very distinctive $|IF|$ as represented in Fig. 5b. The IA will have high values for the areas with higher contrast and therefore in the ideal case the histogram of the IA will have two distinctive peaks: One for the retinal background and one for the edge of the vessels, as seen in Fig. 5c. One of the most distinctive features of vessel-like features is their directionality, which is captured by the IF angle. The direction of change will be roughly the same for an elongated structure like a vessel and therefore the angle of the IF will generate a highly peaked histogram, as seen in Fig. 5d.

Figure 6 shows the histogram of the AM-FM representation for a dark rounded region such as MAs or dot-blot hemorrhages. The lesion is characterized by the IF with large values at the edge of the lesion and low values inside and outside the lesion, as depicted in Fig. 6a. Just as in the case of the vessels, the resulting $|IF|$ histogram has a clear peak for the high-frequency values (Fig. 6b). The IA histogram contains two peaks, one for the contrast changes in the background and one for the contrast changes on the edges of the lesion, as seen in

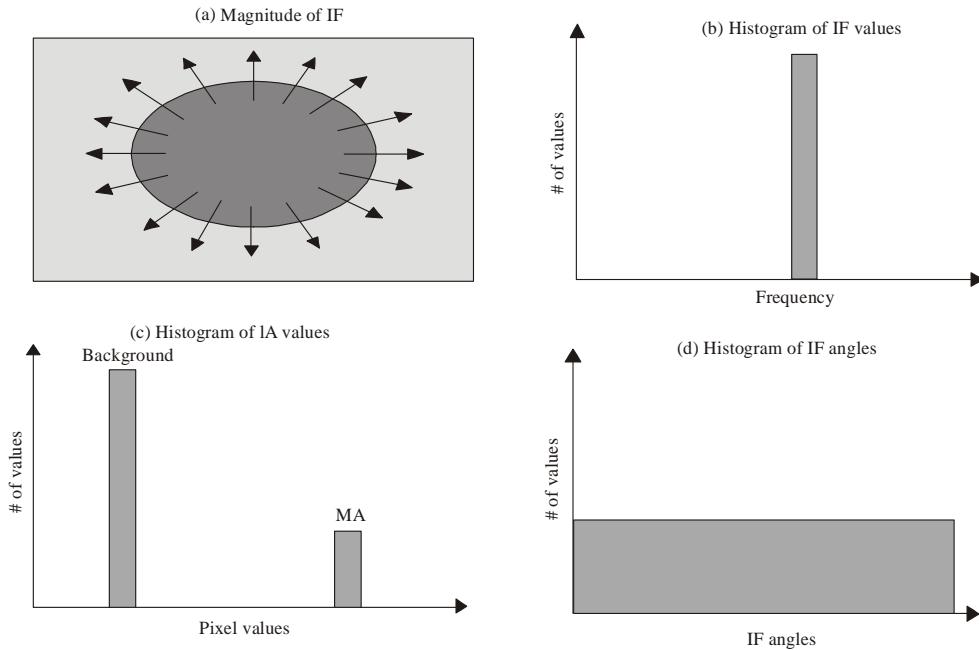


Fig. 6: Conceptual AM-FM analysis for a rounded dark lesion, (a) Instantaneous frequencies on top of lesion, (b) Instantaneous frequency histogram, (c) Instantaneous amplitude histogram, (d) IF angle histogram

Fig. 6c. This IA histogram is similar to the one for the vessel, but since MAs are smaller than vessels, the number of pixels with high contrast will be smaller and therefore the histogram will have a smaller peak that represent the MAs. Finally, one of the biggest differences of vessels and MAs is seen on the IF angle. In the ideal case of a perfect circular shape where all the angles of the IF are represented (Fig. 6a), the histogram for the angles would be uniform, since all angles of the IF are represented.

These two examples illustrate the way in which AM-FM is able to obtain different signatures for each of the two analyzed structures. By combining the outputs of the 3 estimates, any structure with different shape, color and size can be characterized. We are conscious that retinal images present additional information such as noise or blurring which is not considered in the ideal cases presented above, but by using appropriate statistical measurements to represent the AM-FM estimates, high classification accuracy can be obtained.

Performance evaluation: We conduct a set of experiments on the normally available datasets which is used for this purpose to evaluate the performance of the proposed approach with the existing. In addition, algorithm performance was also measured with Receiver Operating Characteristic (ROC) curves. A ROC curve is a plot of true positive fractions (Se) versus false positive fractions (1-Sp) by varying the threshold on the probability map. The closer a curve approaches the top

left corner, the better the performance of the system. The area under the curve, which is 1 for a perfect system, is a single measure to quantify this behavior.

CONCLUSION

This Method is based on a NN scheme for pixel classification, being the feature vector representing each pixel composed of gray-level, moment invariants-based features and AM-FM texture features. The demonstrated effectiveness and robustness, together with its simplicity and fast implementation, make this proposed automated blood vessel segmentation method a suitable tool for being integrated into a complete pre screening system for early DR detection.

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