Abstract

This work describes a new framework for automatic analysis of optic fundus non-mydriatic images, focusing on the segmentation of the blood vessels by using pixel classification based on pattern recognition techniques. Each pixel is represented by a feature vector composed of color information and measurements at different scales taken from the continuous wavelet (Morlet) transform as well as from mean and order filtering applied to the green channel. The major benefit resulting from the wavelet application to the optic fundus images is its multiscale analyzing capability in tuning to specific frequencies, thus allowing noise filtering and blood vessel enhancement in a single step. Supervised classifiers are then applied to label each pixel as either a vessel or a non-vessel. Two different strategies to select the training set have been devised: (1) the blood vessels of a sample image are completely drawn by hand, leading to a labeled image (i.e. vessels × non-vessel pixels) which is used to train the classifier, to be applied to other images; (2) the vessels located in a given small portion of the target image are drawn by hand and the remaining fundus image is segmented by a classifier trained using the hand-drawn portion to define the training set. The latter strategy is particularly suitable for the implementation of a semi-automated software to be used by health workers in order to avoid the need of setting imaging parameters such as thresholds. Both strategies have been extensively assessed and several successful experimental results using real-case images have been obtained.

1. Introduction

Optic fundus (Figure 1) assessment has been widely used by the medical community for diagnosing vascular and non-vascular pathology including those which present abnormalities associated with the vascular tree, the fovea, the optic disk and retina. Blood vessel inspection may reveal hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke [8]. The commonest reason for blindness is diabetic retinopathy. However early recognition of changes to the blood vessel patterns can prevent major vision loss as early intervention becomes possible [13, 15]. Endeavoring to reduce the effect of proliferative diabetic retinopathy includes obtaining and analyzing images of the optic fundus at regular intervals such as every six month to one year. Identification of vascular anomalies represent a large portion of the assessment carried out by ophthalmologists, which is time consuming and in many cases does not show any anomalies at the initial visit. To provide the opportunity for initial assessment to be carried out by community health workers, computer based analysis has been introduced, which includes assessment of the presence of microaneurysms and changes in the blood flow/vessel distribution due to either vessel narrowing, complete occlusions or new vessel growth. Automated assessment of blood vessel patterns is now being extended from the assessment of fluorescein angiograms to non-mydriatic camera images [7, 11]. This work presents a new method, that improved on our previous work, for performing blood vessel segmentation based on the wavelet transform and statistical pattern recognition [7, 9].

An automatic assessment for blood vessel anomalies of the optic fundus requires initially the segmentation of the vessels from the background, so that suitable feature extraction and processing may be performed. Despite several methods having been developed for vessel segmentation, we seek a more accurate result, which addresses improvements in the identification of the vessels and applies this to non-mydriatic images. In addition, it is important to have segmentation algorithms that do not critically depend on configuring many parameters to allow untrained commu-
nity health workers to utilize this technology. The framework described here represents an improvement to the previous approaches in that the algorithm depends only on a manually segmented image or a portion of it, thus meeting our requirements.

Previously [9] we dealt with this problem by applying both mathematical morphology and Wavelet transform approaches. However, the scale parameter was fixed for the wavelet approach resulting in the loss of some detail that might be detected if some additional scale parameters were used. Here we propose a method for blood vessel segmentation that extract features from pixels and perform their classification through pattern recognition using several wavelet scales. Each pixel is represented by a feature vector including color information and measurements at different scales taken from the continuous wavelet (Morlet) transform and from mean and order filtering applied to the green channel. This (green channel) presented the best contrast between the vessels and the background. The resulting feature space was used to classify each pixel as either a vessel-pixel or a non-vessel pixel. Two different strategies for defining the training set have been assessed.

In order to reduce the noise effects associated with the processing, the input image is pre-processed by a $5 \times 5$ mean filter. It is worth mentioning that due to the circular shape of the non-mydriatic image boundary, which is computationally represented as a matrix, we should not consider the pixels outside the region-of-interest, nor its boundary in order to avoid boundary effects.

2. Methods

2.1. General framework

Generally, every object classification comprises the step of enumerating its properties, which may be subjective and strongly observer dependent. For image processing and pattern analysis purposes, properties are referred to as numerical measures taken from an object by using specific mathematical tools. These properties are quantified in order to provide an automatic and objective basis for evaluation. Each tool determines a particular property, the so called feature, which may correspond to a real, complex, integer or Boolean scalar or vector.

Given a set of features according to the previously chosen tools, the object features extraction process can be thought of as a series $P$ of transformations $T_i$; taking the object into a series of features $X_k$; $k = 1, 2, ..., M$. Each combination of features represents a feature vector and its components are the vector basis set of the feature space.

In this work, the image pixels of a fundus image are viewed as $N$ objects represented by feature vectors that allow the application of statistical classifiers in order to segment the image. In this case, two classes are considered, i.e. vessel $\times$ non-vessel pixels. The training set for the classifier is derived by a hand-drawn segmentation of a sample image or of a portion of it, i.e. pixels segmented by hand are labeled as vessels while the remaining pixels are labeled as non-vessels.

2.2. Segmentation Features

2.2.1. Color. There are different ways of obtaining the ocular fundus image, such as with non-mydriatic cameras or through angiograms [10]. Non-mydriatic cameras generally provide color images. Our previous approach [9] was applied to angiogram grey-level images, while this work takes advantage of color information to perform image segmentation.

There were attempted CMYK-based color spaces and RGB-based color spaces, but when RGB components were visualized separately, the green channel showed the best vessels/background contrast off, whereas, the red channel, showed low contrast, being much more noisy, while the blue channel provided no information. In fact, whatever values expressed in RGB-based color space represent the amount of red, green and blue light that are reflected from such an image. The RGB channels may be physically thought of as colored filters, so as to absorb the respective wavelength range in the visible electromagnetic spectrum. Thus, red and blue components due to the blood widespread presence on background would be filtered by the Red and Blue
channels, providing no contrast, whilst the green components, which are practically found just within vessel-pixels (because veins are green), would be filtered by the Green channel, providing the best contrast, despite blood-red existence within vessel-pixels. Therefore, the green channel was selected to be processed by the wavelet and image filters, as well as to compose the feature vector itself, i.e. the green channel intensity of each pixel is taken as one of its features. There has been work done [4] on the so-called red free images for the same reasons aforementioned.

2.2.2. The mean filter and the order filters. Due to the noticeable gradient of intensities spreading over all the fundus image, the result of both the mean filter and order filter were adopted as features in order to take into account the information regarding the specific pixel neighborhood. Because of the importance of this information, statistical order and mean filtering was applied to the green channel image, with the resulting values taken as components for the feature vector of each pixel.

2.2.3. Wavelet transform features. Originally devised for suitably analyzing non-stationary and inhomogeneous signals, the time-scale analysis took place to accomplish unsolvable problems within the Fourier framework, based on the continuous wavelet transform (CWT). The CWT is a powerful and versatile tool that has been applied to many different image processing problems, from image coding [12] to shape analysis [3]. This success is largely due to the fact that wavelets are especially suitable for detecting singularities (e.g. edges) in signals [6], extracting instantaneous frequencies [1], and performing fractal and multifractal analysis. Furthermore, the wavelet transform using the Morlet wavelet, also often referred to as Gabor wavelet, has played a central role in increasing our understanding of visual processing in different contexts from feature detection to face tracking. This wavelet has already proven to be a useful tool for the segmentation of fundus images using a single scale thresholding-based scheme [7, 9]. In this work, we improved the obtained results by integrating the information of several scales and other wavelet parameters.

The notation and definitions in this section follows [2]. The real plane \( \mathbb{R} \times \mathbb{R} \) is denoted as \( \mathbb{R}^2 \), and the vectors are represented as bold letters, e.g. \( \mathbf{x}, \mathbf{b} \in \mathbb{R}^2 \). Let \( f \in L^2 \) be an image represented as a square integrable (i.e. finite energy) function defined over \( \mathbb{R}^2 \). The continuous wavelet transform \( T_{\psi}(\mathbf{b}, \theta, \alpha)(\mathbf{x}) \) is defined as:

\[
T_{\psi}(\mathbf{b}, \theta, \alpha)(\mathbf{x}) = C_\psi^{-1/2} \frac{1}{\alpha} \int \psi^*(a^{-1}r_{-\theta}(\mathbf{x} - \mathbf{b}))f(\mathbf{x})d^2 \mathbf{x}
\]

where \( C_\psi, \psi, \mathbf{b}, \theta \) and \( \alpha \) denote the normalizing constant, analyzing wavelet, the displacement vector, the rotation angle and the dilation parameter, respectively. \( \psi^* \) denotes the complex conjugate. Combining the conditions for both the analyzing wavelet and its Fourier transform of being well localized in the time and frequency domain plus the requirement of having zero mean, one realizes that the wavelet transform provides a local filtering at a constant rate \( \frac{\Delta f}{\Delta \omega} \), indicating its great efficiency as the frequency increases, i.e. as the scale decreases. This property is what makes the wavelet effective for detection and analysis of localized properties and singularities [1], such as the blood vessels in the present case.

From several available analyzing wavelets, for instance, the 2D Mexican hat and the optical wavelet, we chose the Morlet wavelet for the purposes of this work, due to its directional selectiveness capability in detecting oriented features and fine tuning to specific frequencies. This latter property is especially important in filtering out the background noise of the non-mydriatic images. The 2D Morlet wavelet is defined as:

\[
\psi_{M}(\mathbf{x}) = \exp(jk_0 \cdot \mathbf{x})\exp(-\frac{1}{2} |A\mathbf{x}|^2) \tag{2}
\]

where \( j = \sqrt{-1} \) and \( A = \text{diag}[\epsilon^{1/2}, 1], \epsilon \geq 1 \) is a \( 2 \times 2 \) diagonal array that defines the anisotropy of the filter, i.e. its elongation in some direction [1]. In the Morlet equation (2), which is actually a complex exponential modulated Gaussian, \( k_0 \) is a vector that defines the frequency of the complex exponential.

Considering the directional aspect of the Morlet transform, it was expected that pixels within some oriented entity, say vessel domains, should respond strongly to the passage of the Morlet transform for certain values of scale and orientation, whilst background pixels should not.

For each considered scale value, the Morlet wavelet transform is computed spanning from 0 up to 170 degrees at steps of 10 degrees. At each rotational step, the resulting transform matrix is updated taking the maximum value obtained so far at each pixel, in such a way as, finally, for each scale, to retrieve the highest response at each pixel for the transform thus performed.

The \( \epsilon \) parameter has been set larger than 1 in order to make the filter elongated and \( k_0 = [0, 3] \), i.e. a low frequency complex exponential with few significant oscillations. These two characteristics have been chosen in order to enable the transform to present stronger responses for the coefficients associated with the blood vessels. The modulus of the wavelet transform at each pixel is then taken as a pixel feature. In all our experiments, we have used two different scales (i.e. 4 and 8) and, for each scale, two different values of \( \epsilon \) (i.e. 2 and 8), leading to 4 wavelet coefficients per pixel.
2.2.4. Normalization. Given the dimensional nature of the features forming the feature space, one must bear in mind that this might give rise to errors in the classification process, as the units chosen might affect the distance in the feature space.

Since the feature space elements may be considered as random variables, we may apply a transformation in order to obtain a new relative random variable, redefined in a dimensionless manner.

A strategy to obtain a new random variable with zero mean and unit standard deviation, yielding, in addition, dimensionless features, is to apply the normal transformation to the feature space. The normal transformation is defined as [3]:

$$\hat{X}_j = \frac{X_j - \mu_j}{\sigma_j}$$  \hspace{1cm} (3)

where $X_j$ is the $j^{th}$ feature assumed by each pixel, $\mu_j$ is the average value of the $j$-th feature and $\sigma_j$ is the associated standard deviation.

2.3. Supervised Classification for Segmentation

Supervised classification has been applied to obtain the final segmentation, with the pixels classes defined as $C_1 = \{\text{vessel-pixels}\}$ and $C_2 = \{\text{non-vessel pixels}\}$. Three classifiers have been tried, namely minimum distance to prototype, Bayesian (assuming normal distribution) and k-nearest neighbors (e.g. refer to [16]). The best results, which are discussed in this work, have been provided by the latter, one evidence suggesting that we had non-linearly separable classes (e.g. a mixture of gaussians).

In order to obtain the training set, a fundus image has been manually segmented, thus allowing the creation of a labeled training set into 2 classes $C_1$ and $C_2$ (i.e. vessels and non-vessels). In this work, the hand-drawn vascular tree provided by the ophthalmologist has been used - our training pattern - so that we obtained its feature space. Two different strategies for deriving the training set have been tried:

1. One sample image has been completely segmented and a sub-set of its pixels, randomly taken, are used to train the classifier. This can then be used to classify other images. Figure 2(a) shows the manually segmented image used in this paper. A straightforward generalization of this approach is to consider several images completely segmented by hand in order to derive the training set;

2. Only a small portion of a sample image is manually segmented. The labelled pixels are then used to train the classifier, which is applied to the same image in order to conclude its segmentation. This strategy has been devised so that a semi-automated fundus segmentation software may be developed, in which the operator only has to draw a small portion of the vessels over the input image or simply click on several pixels associated with the vessels. The remaining image is then segmented based on this partial training set without the need of tuning any additional parameters. Figure 2(b) shows a partially segmented image (by hand) used in our experiments to illustrate this technique. This approach is interesting since it requires a small effort from the operator, which is compensated by the fact that image peculiarities (e.g. due to camera model and settings) are directly incorporated by the classifier. Notice that this method should be repeated for every new image.

Figure 3 illustrates the discriminative power of the wavelet features showing the feature space defined using two different scales and obtained from the segmented image 2(a) (the points represent vessels (gray points) × non-vessels (dark points) pixels). Although the classes overlap for two dimensions, this fact is circumvented by the use of a higher dimensionality of the feature space (obviously, a too high dimension is not used in order to avoid the problem of dimensionality).

2.4. Post-processing

The output produced by the classifier leads to a binary image where each pixel is labeled as vessel or non-vessel, which is illustrated in Figure 4.

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, the main shape structure used to characterize the blood vessels is its skeleton, which allows shape analysis and comparison among sets of fundus images in a standard manner, e.g. for the estimation of the fractal dimension and other shape measures [7].

In order to accomplish these tasks, morphological operations have been applied, beginning by area open to eliminate small noisy components. The vessels were completely filled by morphological dilation and area close. Finally, the vessels structure was extracted as a skeleton [3] of the resulting image to display the preserved vessel structure. The multiscale skeletonization algorithm based on exact dilations has been applied in this last step [3].

3. Experimental Results

The use of a non-mydriatic camera provides an interesting and versatile way of assessing eye problems associated
with diabetes. Therefore our work has concentrated on automated segmentation of the retinal vasculature using images obtained from a non-mydriatic camera and captured with a 30mm SLR Nikon camera and subsequently digitized by a standard scanner. 31 images have been analysed, from which some were diabetic but did not have neovascularisation. Nevertheless, some of the images showed either no clinical abnormality or the presence of microaneurysms, haemorrhages, cataract vessel occlusion and lipid spots. The assessed images included real-case problems such as photographic artifacts.

The new framework has been successfully applied to these real cases and some results are shown in this section. Firstly, we show the results where the classifier has been trained using the image in Figure 2(a), which are shown in the Figures 5(a)-(d) (the the training image is different from the test ones).

There appear some short disconnected structures in Figures 5(a)-(d). Some among them are noise, however another ones are vein structures. Future endeavoring on the pos-processing step may improve such results by thoroughly eliminating noises and connecting all the disconnected components.

The segmentation result using the second training strategy is shown in Figure 6(a)-(d). In this case, the segmenta-
tion has been performed in the same image, illustrating the feasibility of such approach where only a small portion of the image is manually drawn and the segmentation is concluded by the system.

4. Discussion

Fluorescein angiograms have two disadvantages in that they can only be obtained by specialists in ophthalmology clinics and they may have adverse side effects for the patient. Therefore optic fundus analysis is moving to the use of non-mydriatic images, which is non-invasive and has in the hands of ophthalmologists a comparable rate of success in identifying complications associated with diabetes [5]. In rural and remote areas, there is a lack of clinical specialists and initial screening of optic fundus complications associated with diabetes can be provided by community health workers. As the correct identification of neovascularization is less than 50% for health care workers [14], automated approaches are being devised for implementing in rural clinics. Our work and that of others has investigated the segmentation of angiographic images [9, 17] and non-mydriatic images [7]. The approach reported here improved on previous results by reducing the level of interaction required with the segmentation program, providing a useful tool for non-specialists such as community health workers in assessing fundus complications associated with diabetes.

5. Concluding Remarks

Automated segmentation of non-mydriatic images provides the basis for automated assessment by community
health workers. Skeletonized images of the vessel pattern of the ocular fundus can be analyzed mathematically using nonlinear methods such as fractal [7] and multifractal [11] analysis based on the wavelet transform and provides a numeric indicator of the extent of neovascularization. Our ongoing work aims at applying the shape analysis and classification strategies described in [7] to the segmented vessels produced by method described in this work. The advantage of this method is that it can be used to assess the automatic segmentation by comparing the shape measures to those extracted from the ground-truth (i.e., manually segmented images). The method introduced here presents a main drawback regarding the results with respect to the optic disk, whose outline is sometimes taken as vessel by the classifier (see Figure 5(a) and (b)). We have been addressing this problem and our findings regarding this issue will be reported in due time.

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