IJIRR

International Journal of Information Research and Review
Vol. 03, Issue, 04, pp. 2109-2111, April, 2016

Review Article

"BLOOD VESSEL SEGMENTATION FROM COLOR RETINAL IMAGES USING UNSUPERVISED TEXTURE CLASSIFICATION"

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ARTICLE INFO

Article History:

Received 26th, January 2016
Received in revised form
15th, February 2016
Accepted 20th, March 2016
Published online 27, April 2016

Keywords:

Medical image, Texture classification, Gabor energy filter bank, FCM clustering, Image segmentation.

ABSTRACT

Automated blood vessel segmentation is an important issue for assessing retinal abnormalities and diagnoses of many diseases. The segmentation of vessels is complicated by huge variations in local contrast, particularly in case of the minor vessels. The method of texture based vessel segmentation to overcome this problem. A bank of Gabor energy filters are used to analyze the texture features from which a feature vector is constructed for each pixel. The Fuzzy C-Means (FCM) clustering algorithm is used to classify the feature vectors into vessels or non-vessel based on the texture properties. From the FCM clustering output we attain the final output segmented image after a post processing step.

INTRODUCTION

Eyes are organs that detect light. Different kinds of light-sensitive organs are found in a variety of animals. The simplest eyes do nothing but detect whether the surroundings are light or dark, which is sufficient for the entrainment of circadian rhythms but can hardly be called vision. More complex eyes can distinguish shapes and colors. The visual fields of some such complex eyes largely overlap, to allow better depth perception (binocular vision), as in humans; and others are placed so as to minimize the overlap, such as in rabbits and chameleons (Staal *et al.,* 2004; Martinez-Perez *et al.,* 2007; Anitha *et al.,* 2009). Diabetes affects the circulatory system of the retina. The earliest phase of the disease is known as background diabetic retinopathy. In this phase, the arteries in the retina become weakened and leak, forming small, dot-like hemorrhages (Sonal *et al.,* 2012). These leaking vessels often lead to swelling or edema in the retina and decreased vision. The next stage is known as proliferative diabetic retinopathy in which circulation problems cause areas of the retina to become oxygen-deprived or ischemic. Changes in retinal vasculature, such Hemorrhages, Neovascularization, Cotton-wool spots and blockages (as shown in figure 1) are important indicators of diabetic retinopathy (Staal *et al.,* 2004; Jelinek *et al.,* 2007).

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The affect of diabetic retinopathy on vision varies widely, depending on the stage of the disease. Some common symptoms of diabetic retinopathies are listed below; however, diabetes may cause other eye symptoms.

- Blurred vision (this is often linked to blood sugar levels)
- Floaters and flashes
- Sudden loss of vision

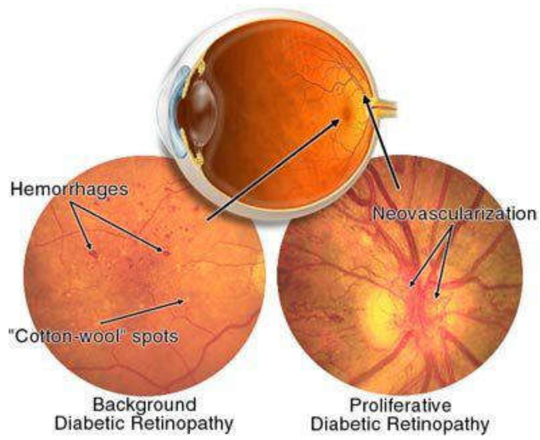

Figure 1. The affect of diabetic retinopathy

Diabetic patients require routine eye examinations so related eye problems can be detected and treated as early as possible. Most diabetic patients are frequently examined by an internist or endocrinologist who in turn works closely with the ophthalmologist (Mendonça and Campilho, 2006; Tobin *et al.,* 2007). The automated detection of blood vessels is very important as ophthalmologists can potentially screen larger populations for vessel abnormalities. Information about blood vessels in retinal images can be used in grading disease severity or as part of the process of automated diagnosis of disease (Solouma *et al.,* 2002; Spencer *et al.,* 1996). Automated retinal segmentation is complicated by the fact that width of the retinal vessels can vary from large to very small, and the local contrast of vessels is unstable, especially in unhealthy retinal images (Hoover *et al.,* 2000). Gaussian and L*a*b perceptually uniform color spaces consider with the original RGB images for texture feature extraction. To extract features, a bank of Gabor energy filters with three wavelengths and twenty-four orientations is applied in each selected color channel. Then the texture image is constructed from the maximum response of all orientations for a particular wavelength in each color channel. From the texture images, a feature vector is constructed for each pixel. These feature vectors are classified using the Fuzzy C-Means (FCM) clustering algorithm (Sonal *et al.,* 2012; Timo Ojala *et al.,* 1999).

Proposed system

A. Working Principle

The proposed method for blood vessel segmentation which is based on the texture property analysis of vessel and non vessel parts in the color retinal images. The reasons are as follows. Firstly, due to large variation of local contrast in the retinal images, texture analysis is more appropriate to extract features from vessel and non vessel parts in the retinal images. Secondly, a color texture is a spatio-chromatic pattern and can be defined as the "distribution of colors over a surface"; therefore, incorporating color into texture analysis is enhancing the procedure. The original retinal images are in RGB color space which is not perceptually uniform and Euclidean distances in 3D RGB space do not correspond to color differences as perceived by humans. In addition, perceptually uniform color spaces are very effective in rotation invariant color texture analysis. So, perceptually uniform color spaces along with original RGB color channels are used to extract texture features. Figure 2 portrays the overall technique of proposed method.

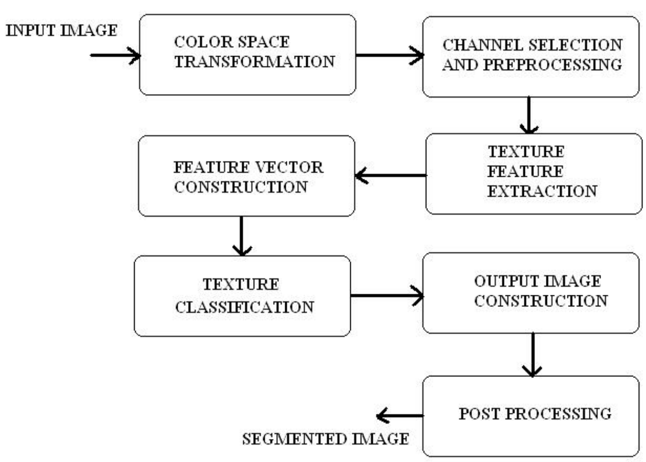

Figure 2. The vessel segmentation model

At first, the transformation of original RGB image apply into Gaussian and L*a*b color space. The two components of Gaussian color space Ê and Êλ, luminance L from L*a*b color space and green channel G from RGB color space due to the higher contrast of vessel and background which is convenient for texture analysis. Now Adaptive Histogram Equalization (AHE) method to these four different color channel images for contrast enhancement. For each of these color channels, we apply a bank of Gabor filters with twenty-four orientations and three wavelengths for texture feature extraction. The texture image is constructed in each color channel for every wavelength considering the maximum response of all twenty-four orientations. These texture images are used to analyze the number of clusters which later will be used as classifier input. Consequently, twelve texture images constructed for each original retinal image and a feature vector for every pixel mapping each pixel position of all these texture images. These feature vectors are classified as a vessel or background part using unsupervised FCM clustering algorithm. From the output of the FCM clustering algorithm, 2D matrix original image is constructed with cluster numbers which have the highest membership values. Finally ultimate segmented image is produced with converting the cluster numbers into binary values considering the cluster Centroid values.

B. Image Segmentation

Segmentation refers to the grouping of an image into individual entities where an object is distinguished from its surrounding in a scene. It allows a quantitative measurement of the geometrical changes of arteries, tortuosity or lengths and provides the localization of landmark points such as, bifurcations needed for image registration. Therefore, automated vasculature measurement could reduce both the expenditure of resources in terms of specialists and the examination time and provide an objective, precise measurement of retinal blood vessel structure and other pathologies, which motivate the development of a robust vessel segmentation method (Jelinek *et al.,* 2007). A central feature in such diagnosis is the appearance of blood vessels in retinal images. Segmentation of these vessels enables eye care specialists to screen larger populations for vessel abnormalities. However automated retinal image segmentation is complicated by the fact that the width of retinal images can vary from very large to small, and that the local contrast of vessels is unstable(inhomogeneous background). Thresholding defines a region of interest before image segmentation will limit the processing of the defined region so no computing resource is wasted for other irrelevant areas. This also reduces the amount of editing needed after image segmentation because object boundaries are generated within the defined regions.

Interactive Thresholding

This technique uses two values to define the threshold range. The thresholds are adjusted interactively by showing all pixels within the range in one color and all pixels outside the range to a different color. Since the thresholds are displayed in real-time on the image, the threshold range can be defined locally and varied from slice to slice. All pixels within the range are segmented to generate the final boundaries.

Texture-Based Segmentation

While image texture has been defined in many different ways, a major characteristic is the repetition of a pattern or patterns over a region. The pattern may be repeated exactly, or as a set of small variations on the theme, possibly a function of position. For medical images, because objects are normally certain type of tissues, such as blood vessels, brain tissue, bones and etc, they provide a rich set of texture information for image segmentation. For some objects with strong texture, texture based segmentation generates more accurate object boundary than thresholding based methods.

C.Texture feature extraction

Texture generally describes second order property of surfaces and scenes, measured over image intensities. The aim of the feature extraction stage is pixel characterization by means of a feature vector. Gabor filters with twenty-four orientations and three wavelengths are used for texture feature extraction for each of the color channels. Twelve texture images are constructed for each original retinal image considering the maximum response. These are used to analyze the number of clusters which are classifier input. The 12 length feature vector is constructed for every pixel mapping each pixel position of all the texture images. The method is very efficient in detecting both major and minor blood vessels. A Gabor filter has weak responses along all orientations on the smooth surface. On the other hand, when it positioned on a linear pattern object (like a vessel) the Gabor filter produces relatively large differences in its responses when the orientation parameter changes.

D. Classification

This defines a grouping of all the categories in 2 disjoint teams. This grouping is then wont to train a SVM classifier within the root node of the choice tree, victimization the samples of the primary cluster as positive examples and therefore the samples of the second cluster as negative examples. The categories from the primary clump cluster are being assigned to the primary (left) subtree, whereas the categories of the second clump cluster are being assigned to the (right) second subtree. The method continues recursively till there's just one category per cluster that defines a leaf within the call tree. Many of the hemorrhages are connected (continuous) with the retinal vessels. Because many of the false positives in our approach are parts of retinal vessel, an alternative approach would be to mask out all blood vessels using one of the common vessel segmentation methods (Himaga *et al.,* 2004). It attractive at first consideration, also masked out many of the large hemorrhages we are trying to detect in the first place. Splats are created by over-segmenting images using watershed or toboggan algorithms Conventional image over segmentation on a regular grid generates so called "super pixels" a similar concept to "splats." But super pixels are roughly homogeneous in size and shape, resulting in a lattice pattern. In contrast, a splat-based approach divides images into an irregular grid, depending on properties of target objects to be detected.

Conclusion

These exists various challenges in the automatic detection of the hemorrhages. It is hard to distinguish hemorrhage from background variations due to its low contrast [4]. Detection of hemorrhage can be confused by other dark areas in the image such as the microaneurysms, blood vessels and fovea. Hemorrhages are in variable size and often they are so small that can be easily confused with the image noise or microaneurysms and there is no standard database available to classify hemorrhage by shape. The false detection is done in the case when the blood vessels are overlapping or adjacent with hemorrhages. So the effective methodology to detect hemorrhage is needed.

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