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Retinal Blood Vessel Segmentation using Ripplet Transform and FCM Clustering

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Abstract* - Eye is very crucial part of human body. The appearance of the retinal blood vessel can be significant diagnostic indicator of various disorders of the eye like diabetic retinopathy,Hypertension, Central Retinal Artery Occlusion. Image Segmentation is first step of most of image processing applications. Edge, point, line, boundary, texture and region detection are the various forms of image segmentation. This work proposes an algorithm to detect Retinal Blood vessels effectively. Ripplet transform and FCM can be used for feature extraction due to its efficiency in representing edges and textures. Experiments in texture classification and image retrieval demonstrate that the ripplet transform based scheme outperforms wavelet and ridgelet transform based approaches.

Keywords-Image Enhancement, Image segmentation, Ripplet Transform, morphological reconstruction, FCM.

I. INTRODUCTION

The eye is the most easily accessible part of the human body where arterial and venous blood vessels can be studied in vivo noninvasively. The appearance of the retinal blood vessel can be important diagnostic indicator of various disorders of the eye. This research work focuses on the development of a computer-assisted diagnostic system for ophthalmic disorders.

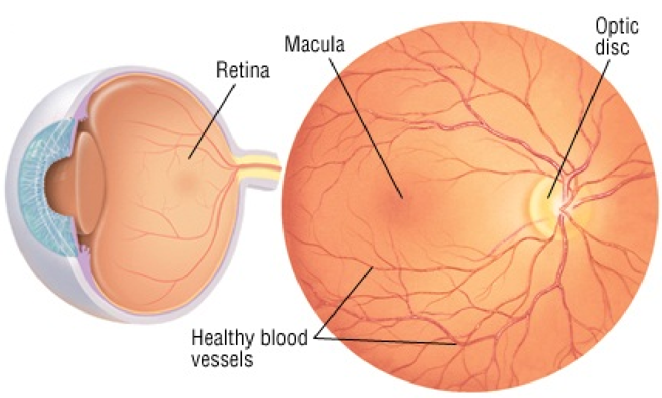


Fig. 1.1 Healthy Retina

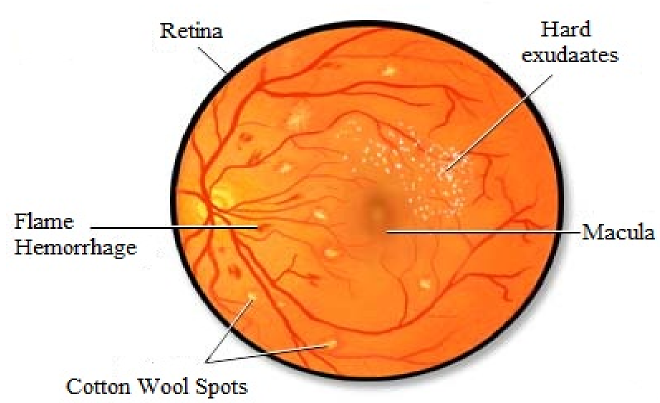


Fig. 1.2 Damaged retinal blood vessels due to hypertension

II. SYSTEM MODEL

A. Image Segmentation

A process of subdividing an image into the consequents parts or objects in the image is known as image segmentation. So the main purpose of subdividing an image in to its consequent parts or objects present in the image is that we can further analyze each of object or consequent present in the image to extract some information. That information is useful for high level machine vision applications. In other words image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Edge, point, line, boundary, texture and region detection are the various forms of image segmentation. The aim of this research work is to extract some information from the retinal image so that, that information can be used for high level image understanding operations. Retinal Blood Vessel segmentation is the process of partitioning a digital retinal blood vessel image into multiple segments (sets of pixels, also known as super pixels).Retinal blood vessel segmentation of retinal blood vessels attributes, such as length, width and/or branching pattern and angles are utilized for diagnosis, screening, treatment, and evaluation of various diseases such as diabetes, hypertension etc.It is observed from the literature survey that the retinal blood vessels of patients suffering from hypertension, diabetes, cardiovascular diseases exhibit morphological changes and deformations in the blood vessel.These minute changes in the retinal blood vessels are not easy to detect. The retinal images are degraded due to imaging conditions that makes the segmentation of the blood vessels difficult [2].Manual segmentation of retinal blood vessels is a long and tedious task which also requires training and skill. It is commonly accepted by the medical community that automatic quantification of retinal vessels is the first step in the development of a computer-assisted diagnostic system for eyedisorders. Many efforts have been made and various methods have been introduced in order to segment retinal images but they are not capable to detect very thin blood vessels so this proposed work is basically introduce to overcome this tedious task. There are two types of segmentation approaches by which segmentation is done.

1. Discontinuity based

2. Similarity based

In discontinuity based approach, the partition or subdivision of an image is carried out based on some abrupt changes in intensity levels in an image or abrupt changes in gray levels of an image. Isolated Point Based Segmentation, Line based Segmentation and Edge based Segmentation are the types of discontinuity based segmentation. In edge based segmentation, segmentation is done by detecting the edges or pixels between different regions that have rapid transition in intensity are extracted and linked to form closed object boundaries [3]. The result is a binary image. Based on theory there are two main edge based segmentation methods- gray histogram and gradient based method. Similarity based approach is slightly different from discontinuity based approach. In this approach pixels in an image are grouped for thresholding, Region growing and Region splitting and merging.

III. PREVIOUS WORK

Image Segmentation becomes difficult due to the variations in the intensities of the image .So, image has been enhanced before segmentation. In earlier cases of image segmentation Fourier transform is been used .However, Fourier transform gives an efficient representation for smooth images but, it is not capable to detect edges present in the image [10].Edges or boundaries of objects cause discontinuity or singularities in image intensity. Wavelet transform [10] has the ability to represent a function with 1D singularity. However, it is not capable to resolve 2D singularities along arbitrarily shaped curves. To overcome the previous limitation ridgelettransform [11] was introduced which is able to represent 1D singularities along arbitrarily shaped curves but, it is not capable to resolve 2D singularities. Then they proposed curvelet transform [1] which is able to represent 2D singularities along smooth curves but able to resolve arbitrarily shaped curves. And thus ripplet transform was introduced.The main aim of image segmentation is to decompose an image in to a number of disjoint regions so that the features within each region have visual similarity strong statistical correlation andreasonably good homogeneity. Mathematical morphology is a technique in which the shape oriented approach treats the image as a set and the kernel of operation known as structuring element. Dilation, erosion, opening, closing, top-hat transformation etc. are morphological operations [2] which are used to extracting, modifying, manipulating the features present in the image based on theirshapes. The process of reconstruction uses a binary morphological reconstruction method called the double threshold operator.

IV. PROPOSED METHODOLOGY

Image quality is the difficulty in capturing image of the ocular fundus thus the image is to be enhanced before the process of segmentation.

A.Ripplet Transform

Ripplet is discontinuity based transform which is generalized form of cuvelet transform [3].For efficient representation of 2D singularities along with arbitrarily shaped cuves or edges of the image ripplet transform is used because it having the following properties:

a) Multi Resolution- It provides hierarchical representation of image and also havingthe ability to approximate the imagesfrom harsh to fine size.
b) Good Localization – It gives the compact support to frequency domain as well as to spatial domain means it localized very efficiently in both frequency and spatial domain.

c) High Directionality – Ripplet function can obtain more directions with the increasing in resolution of image.
d) General Scaling and Support – It has the ability to represent scaling with arbitrary degree and support.
e) Anisotropy –Means it has the ability to extract the singularities along with various curves.
f) Fast Coefficient Decay – Coefficient decay in Ripplet transform is faster than the other transforms.

B. Concept of Ripplets

Curvelet transform has the ability to represent the 2D singularities along with C2 curves.Curvelet uses a parabolic scaling law to show anisotropic directionality [3]. But, there is no clear idea that why parabolic scaling was selected for achieving anisotropic directionality in curvelet. To overcome this, Jun Xu, Lei Yang and Dapeng Wu proposed a new transform called Ripplet transform Type I(Ripplet-I), which is generalize form of curvelet transform. Generalized ripplet transform added two parameters i.e. support c and degree. These parameter provides anisotropic capability to show 2D singularities along with arbitrarily shaped curves. The ripplet function can be generated as:

$\hat{\rho}_{a\vec{b}\theta}\,(\vec{x}) = \rho_{a\vec{0}0}(R_\theta(\vec{x}-,\vec{b})$ (1)

Where$\rho_{a\vec{0}0}$tends to ripplet element functionand $R_\theta = \begin{bmatrix} \cos\theta & \sin\theta \\ -sin\,\theta & cos\,\theta \end{bmatrix}$is the rotation matrix. The function of ripplet in frequency domain is define as

$\hat{\rho}_a(r,\omega) = \frac{1}{\sqrt{c}} a^{\frac{1+d}{2d}} W(a.r) V\left(\frac{a^{\frac{1}{d}}}{c.a}\omega\right)$(2)

Where$\hat{\rho}_a(r,\omega)$tends to Fourier transformof $\rho_{a\vec{0}0}(\vec{x})$, $W(r)$tends to ‘radial window’ on[1/2,2] and $V(x)$is the angular windowon [-1, 1].These two windows partition the polar frequency domain into wedges as shown in Fig. 1.3

The set of functions $\{\hat{\rho}_{a\vec{b}\theta}\}$ is defined as Ripplet functions or ripplets for short, because in spatial domain these functions have ripple- like shapes. c determines the support of ripplets and d is defined as the degree of ripplets. Fig. 1.4 shows ripplets with different c and different d in spatial domain. From Fig. 1.4, we can see that ripplet functions decay very fast outside the effective region, which is an ellipse with the major axis pointing in the direction of the ripplet. The major axis is defined as the effective length and the minoraxis, which is orthogonal to the major axis, is theeffective width. The values of c and d will actually affect the effective length and width of ripplets in

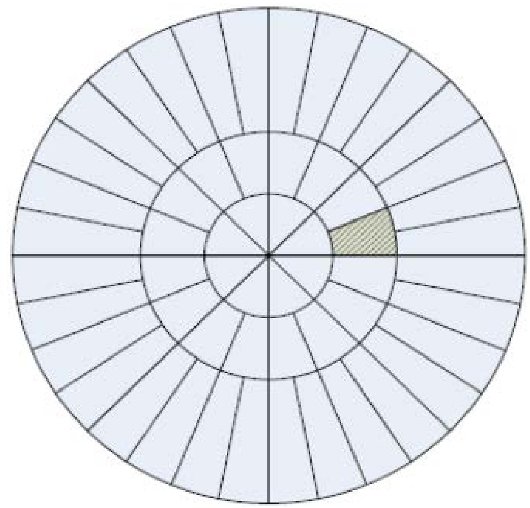
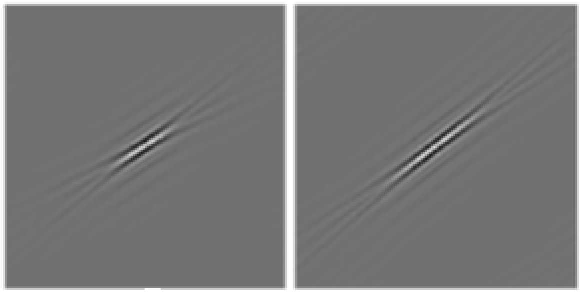


Fig. 1.3 The tiling of polar frequency domain. The shadowed ‘wedge’ corresponds to the frequency transform of the element function.

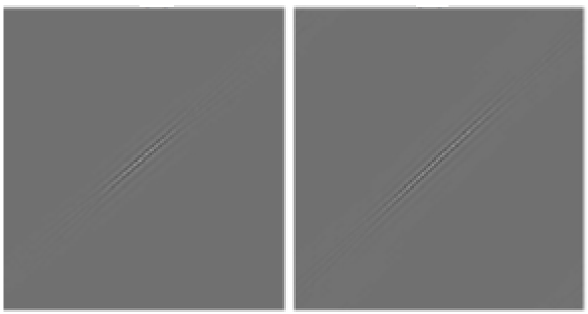
spatial domain. The effective region has the following properties for its length and width: width ≈c x lengthd.

For fixed d, the larger c is, the shorter the width is and the longer the length is. When c is fixed and d gets larger, the width gets shorter and the length is elongated.

The customizable effective region tuned by support c and degree d bespeaks the most distinctive property of ripplets – the general scaling. For c = 1, d = 1, both axis directions are scaled in the same way. So ripplet with d = 1 will not have the anisotropic behavior. For d> 1, the anisotropic property is reserved for ripplet transform. For d = 2, ripplets have parabolic scaling; for d = 3, ripplets have cubic scaling; and so forth. Therefore, the anisotropy provides ripplets the capability of capturing singularities along arbitrary curves. The ripplets as the generalization of curvelet have almost all the properties of curvelet except the parabolic scaling. Ripplets can get multi-resolution analysis of data. For each scale, ripplets have different compact supports such that ripplets can localize the singularities more accurately. Ripplets are also highly directional to capture the orientations of singularities.



(a) (b)



(b) (d)

Fig.1.4 Ripplets in spatial domain with different degrees and supports, which are all located in the center,i.e.,b = 0.(a) a = 3, θ = 3 π /16, c = 1, d = 2, called curveletparticularly.(b) a = 3, θ = 3 π /16, c = 1.5, d = 2. (c) a = 4, θ = 3 π /16, c = 1, d = 4. (d) a = 4, θ = 3 π /16, c = 1.5, d = 4.

C. Discrete Ripplet Transform (DRT)

Digital image processing needs discrete transforms. The discretization of continuous ripplet transform is actually based on the discretization of the parameters of ripplets. For the scale parameter a, we sample at dyadic intervals. The position parameter b and rotation parameter are sampled at equal-spaced intervals.$a, \vec{b}$and$\theta$are substituted with discrete parameters$a_j \overrightarrow{b_k}$ $and\ \theta_l$, which satisfy that

$$a_j = 2^{-j};\ \overrightarrow{b_k} = \left[c.2^{-j}.k_1, 2^{-j/d}.k_2\right]^T$$

and

$$\theta_l = \frac{2\pi}{c}.2^{-[1-1/d]}.l$$

where

$$k = [k_1, k_2]^T, (.)^T$$

Denotes the transpose of a vector and$j, k_1, k_2, l \in \mathbb{Z}$.the degree of ripplets cantake value from R. Since any real number can be approximated by rational numbers, we can represent d with $d = n/m, m \neq 0 \in \mathbb{Z}$.Usually, we prefer$n, m \in N$ and $n, m$are both primes.The 'wedge' corresponding to the ripplet function in the frequency domain is

$$\boldsymbol{H_{j,l}(r,\theta)} = \left\{\boldsymbol{2^j \leq |r| \leq 2^{2j}}, \left|\boldsymbol{\theta - \frac{\pi}{c}.2^{\left|j\left(1-\frac{1}{d}\right)\right|}.l}\right| \leq \boldsymbol{\frac{\pi}{2}2^j}\right\} \quad (3)$$

The parameter c controls the number of directions in the high-pass bands. d controls how the number of directions changes across bands. For fixed c, d helps to control the resolution in directions at each high-pass band. Given d, c controls the number of directions at all high-pass bands. c and d determine the final number of directions at each band together.

The discrete ripplet transform of an M X N image$f(n_1, n_2)$will be in the form of

$$R_{j,\vec{k},l} = \sum_{n_1=0}^{M-1}\sum_{n_2=0}^{N-1} f(n_1, n_2)\overline{\rho_{j,\vec{k}l}(n_1, n_2),} \quad (4)$$

Where $R_{j,\vec{k},l}$are the ripplet coefficients.

The image can be reconstructed through inverse discrete Ripplet Transform

$$\boldsymbol{\tilde{f}(n_1, n_2)} = \sum\nolimits_j \sum\nolimits_{\vec{k}} \sum\nolimits_l \boldsymbol{R_{j,\vec{k},l}\, \rho_{j,\vec{k},l}(n_1, n_2)} \quad (5)$$

Ripplets provide a new tight frame with sparse representations for images with discontinuities along c d curves.

Nonlinear approximation (NLA) of images is adopted as a common comparison approach toquantify the performance of sparse representation of transforms. Considering we have ortho-normal basis and the corresponding coefficients. Then the coefficients are sorted in descending order with respect to themagnitude. The nonlinear approximation is obtained using n-largest coefficients. Since ripplet transform provides a tight frame, the concentration of ripplet coefficients will lead to more accurate approximation in NLA. The faster the coefficients decay, the more compact energy will be allocated to the fewer large coefficients.

Image Segmentation

The segmentation process is done by morphological operator to enhance the image quality. FCM i.e. Fuzzy C-mean clustering, clustering is a technique by which grouping of similar data or objects done between them and these group of similar data or objects known as cluster.FCM is a mathematical morphological technique which allows one piece of data to belong two or more clusters [5].This method was introduced by Ruspini and later extended by Dunn and Bezdek and has been widely used in image processing, pattern recognition and cluster analysis. This method introduces the fuzziness for the belonging of each object and can retain more information of the data set than the hard K-mean clustering algorithm. On the basis of distance between the cluster and the data point FCM assigns membership to each data point corresponding to each cluster center. The summation of membership of data point should be equal to 1. The objective function can be define as

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2, 1 \leq m \leq \infty$$

Where m i.e. fuzziness exponent is any real number which is greater than 1.N tends to number of data. C tends to number of cluster. u_{ij} tends to degree of membership of x_i in the cluster j.$x_i$tends to i^{th} of d- dimensional measured data and c_j tends to d- dimension center of cluster ,$\|*\|$ is any norm expressing the similarity between any measured data and the center.

Fuzzy clustering [5] is obtained from an iterative optimization of the objective function shown above, with the update membership u_{ij} and the cluster c_j by

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$$

$$= \frac{1}{\left(\frac{\|x_i - c_j\|}{\|x_i - c_1\|}\right)^{\frac{2}{m-1}} + \left(\frac{\|x_i - c_j\|}{\|x_i - c_2\|}\right)^{\frac{2}{m-1}} + \cdots + \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$$

Where $\|x_i - c_j\|$the distance from point I to current cluster center j is,$\|x_i - c_k\|$ is the distance from the point i to other cluster center k.

$$C_j = \frac{\sum_{i-1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

The iteration will stop when$\{\left|u_{ij}^{k+1} - u_{ij}^{k}\right|\} < \varepsilon$

Where εtends to termination criterion between 0 and 1, k are the iteration steps.

Advantages of FCM algorithm

- FCM gives result comparatively better than k- means algorithm.
- It gives best result on overlapped dataset.
- In FCM, data point is assigned membership to each cluster as a result of which data point may belong to more than one cluster.

V. EXPERIMENTAL RESULTS

A. Data base used

DRIVE data base of retinal images used as input image which contains 40 color images of retina with 556×584 pixel and 8 bits per color channel.

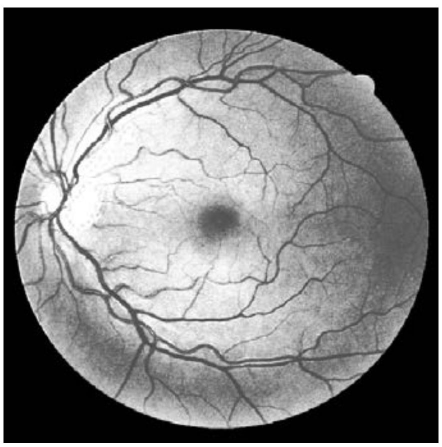
B. Implementation

This proposed method is been implemented using MATLAB version 7.12.0.635. The green channel has the highest contrast with the background so it is selected from the database. This green channel image is been applied as the input image for the DRT and again inverse DRT is been applied to get the reconstructed image. Enhanced image is obtained by varying the values of parameters c and d. With a nonlinear approximation the process of DRT is done and the final enhanced image is been got.

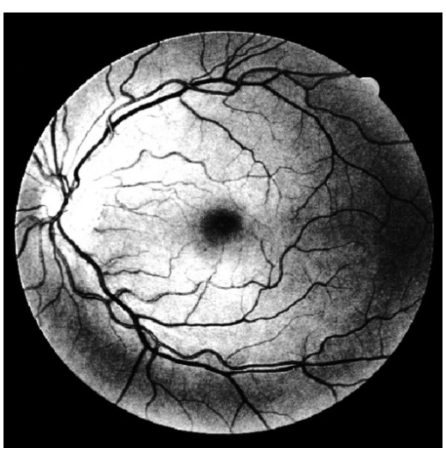
(a)

The calculated PSNR value of the image measured the quality of enhanced image and for the image 1 of DRIVE database which was considered as input, it was found to be 30.28 db. The segmentation process is done by using the FCM i.e. morphological method and which is using the difference between the dilation and erosion operators. The segmented image is been got. To extract the connected components of image the segmented image undergoes reconstruction than got the resulting image which contains connected components.

(b)



(c)



(d)

Fig.1.5 (a) The input image from the DRIVE database, (b) Green channel image of input image, (c) Enhanced image, (d) Segmented image

VI. CONCLUSION

It is clear from above picture frames that Retinal Blood vessels adopting Retinal Blood Vessel Segmentation using Ripplet Transform and FCM the visibility of blood vessels are much better than the previous method. This technique helps in precise analysis of variations in the sizes and shapes of retinal blood vessels which ensure physician to give exact analysis of depth of diseases.

VII. FUTURE SCOPE

Any research work always has scope for further research and betterment. Following are some points on which further research work can be carried out on proposed work.

- Here, Ripplet Transform is used for 2D singularities. A fine tuning of transform will also use for 3D singularities.
- The proposed work is based only on green channel images, the work could be extended to colour images too.

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