A Comparison Study to Evaluate Retinal Image Enhancement Techniques

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***Abstract*— Retinal vessels can show different states of several diseases, making the detection of vessels in retinal images very crucial. Retinal images can be used for other applications such as ocular fundus operations and human recognition. Due to the acquisition process, these images often have low grey level contrast and dynamic range that can seriously affect diagnosis procedure results. In this paper, we present an algorithm for retinal image contrast enhancement based on the second generation of new multi-resolution analysis tool called Curvelet Transform which is faster and simpler than the first version. Curvelet transform has favorable geometric features that provide better representation of edges compare to other widely used multi-resolution tools such as Wavelet. We use a nonlinear function to modify the Curvelet coefficients based on their statistic features. Results of applying this method to a known database, DRIVE, and comparing with previous approaches, proved this method to be effective and helpful for image segmentation.**

***Keywords*— Contrast enhancement, Curvelet transform, retinal image, retinal blood vessel.**

I. INTRODUCTION

Recent studies [1], [2] have shown that quantitative measures of the retinal microvasculature predict cardiovascular disease [4]. Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of several pathologies like hypertension, diabetes, and cardiovascular disease. Also detecting the retinal blood vessels is helpful in several other applications such as biological characterization for person identification, advanced security applications, providing information for ocular fundus survey and diagnosis of primary levels of diabetes and blood pressure. Image processing and data mining techniques, hold promise to provide the novel computational tools to aid this detection [5].

One of the significant problems we encounter in order to detect the blood vessels, is the improper image contrast resulting from the acquisition process. This type of image acquisition leads to retinal images often having a low grey level contrast and dynamic rang. Consequently, preprocessing should be applied in order to overcome this problem.

Several algorithms were introduced for image contrast enhancement, each having advantages in making it suitable for specific purposes. One of the primary algorithm suggested by Zimmerman and Pizer [6], is Histogram Equalization which performs well for regular images, such as human portraits or nature images. Some of the more advanced methods such as unsharp masking introduced by Polesel et al. [7]; Yang et al. [8] and local normalization suggested by Joes et al. [9], have been proposed to enhance the image contrast. Subsequently, other techniques based on the matched filters have also been introduced [10,11,12]. These techniques represent good local contrast enhancers, especially for blood vessel in a small area, but when applied for the whole image, the complexity of computation increases due to the need of various matched filters [14]. Wavelet is one of the wide used multi-scale processing. Wavelets may not be suitable for enhancing the retinal image contrast because they are blind to the smoothness along the edges commonly found in such images [6].

Recently (Candès and Donoho [16]) Curvelet Transform, a new multi-scale transform, was introduced to overcome this problem. Curvelet as a geometrical transform has two important features: anisotropy scaling law and the directionality. These two features made Curvelet capable of sparse representation and handling image singularities better than other multi-scale transforms. Another new transform, Contourlet, introduced by Do and Vetterli [13], has these two features and is also capable of overcoming the Wavelet insufficiency. Based on prior research, Emmanuel Candès et al. [15], introduced the second generation of Curvelet transform which is faster and simpler than the first version. In this paper, we used the second generation of Curvelet transform and modified the Curvelet coefficients by applying a nonlinear function and using some statistic features of these coefficients. Using the Curvelet inverse transform we were able to get enhanced image. Comparing our results to the results of the contrast enhancement techniques, mentioned above, showed the improvement in visualization, contrast enhancement and performance.

The rest of this paper is organized as follows. In the next section, the second generation of Curvelet transform is introduced. After which, the proposed method for retinal image contrast enhancement using second generation of Curvelet is elaborated. In section 4 the experimental results are presented. The last section concludes the work proposed in this paper.

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II. MOTIVATION AND AN OVERVIEW OF CURVELET TRANSFORM

A. *Motivation*

Intense research in the last few years has shown that classical multi-resolution ideas are far from being universally effective. While Wavelets are certainly suitable for dealing with objects where the interesting phenomena, e.g., singularities, are associated with exceptional points, they are ill-suited for detecting, organizing, or providing a compact representation of intermediate dimensional structures because wavelets ignore the geometric properties of objects with edges [15].

Recently, Candès *et al.* developed a new geometric multi-scale transform, the Curvelet transform, which allows an optimal sparse representation of objects with C^2-singularities. The transform can represent edges and singularities along curves much more efficiently than the traditional Wavelet transforms. For a smooth object f with discontinuities along a generic C^2-smooth curve, the best m-term approximation $\tilde{f}_m$ by wavelets thresholding obeys

$$\|f - \tilde{f}_m\|_2^2 \approx m^{-1}\ ,\ m \to \infty \tag{1}$$

while a Curvelet best m-term approximation $\tilde{f}_m^c$ achieves

$$\|f - \tilde{f}_m^c\|_2^2\ \approx\ Cm^{-2}(\log m)^3 \tag{2}$$

and is optimal in the sense that no other representation can yield a smaller asymptotic error with the same number of terms [15].

B. *Digital Curvelet Transform*

In this section, we introduce a so-called second-generation discrete Curvelet transform (DCT) which is simpler and more transparent to apply. Here we explain the wrapping method. Both wrapping and USFFT are described in [15] with more details.

Curvelet coefficients $C^D(j,l,k)$ are simply achieved by the inner product between element $f\ \in L^2(R^2)$ and a Curvelet $\varphi_{j,l,k}^D$ (here and below, the superscript D stands for "digital")

$$C^D(j,l,k) := \sum_{0\le t_1,t_2<n} f[t_1,t_2]\,\overline{\varphi_{j,l,k}^D[t_1,t_2]} \tag{3}$$

where, $C^D(j,l,k)$ is a collection of coefficients, $\varphi_{j,l,k}^D[t_1,t_2]$ denotes a digital Curvelet transform and j,l,k are scale, orientation and translation parameters respectively. In the continuous-time definition, the window U_j smoothly extracts frequencies near the dyadic corona $\{2^j\ \le r \le 2^{j+1}\}$ and near the angle$\{-\pi.2^{-j/2} \le \theta \le \pi.2^{-j/2}\}$. U_j is defined as follows

$$U_j(r,\theta) = 2^{-3j/4}W(2^{-j}r)V\left(\frac{2^{\lfloor j/2\rfloor}\theta}{2\pi}\right) \tag{4}$$

where W and V are radial and angular windows. Coronae and rotations are not especially adapted to Cartesian arrays. Instead, it is convenient to replace these concepts by Cartesian equivalents; here, "Cartesian coronae" based on concentric squares (instead of circles) and shears. This digital tiling is shown in fig. 1 [15].

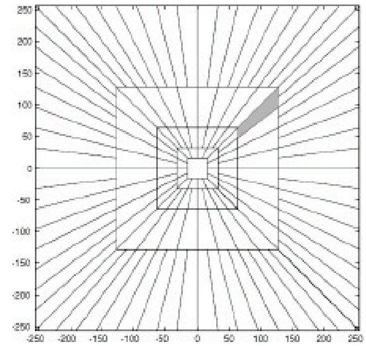

Fig. 1 The figure illustrates the basic digital tiling. The windows $\widetilde{U}_{j,l}$ smoothly localize the Fourier transform near the sheared wedges obeying the parabolic scaling. The shaded region represents such typical wedge.

Here the window is defined as below:

$$\widetilde{U}_{j,l}(\omega) := W_j(\omega)V_j\left(S_{\theta_l}\omega\right) \tag{5}$$

where, S_θ is the shear matrix,

$$S_\theta := \begin{pmatrix} 1 & 0 \\ -\tan\theta & 1 \end{pmatrix}$$

(6)

the angles θ_l are not equispaced but the slopes are, and

$$\tan\theta_l := l.2^{-\lfloor j/2\rfloor}\ ,\ \ l = -2^{-\lfloor j/2\rfloor}, \dots, 2^{-\lfloor j/2\rfloor} - 1 \tag{7}$$

here $\tan\theta_l$ are restricted to the interest of (-1, 1].

C. *Wrapping Method*

The wrapping method assumes a regular rectangular grid to wrap the object. The idea is to first decompose the image into a set of frequency bands, and to analyze each band by a Curvelet transform. The block size can be changed at each scale level. The architecture of the FDCT via wrapping is as follows:

1. Apply the 2D FFT and obtain Fourier samples
   $$\hat{f}[n_1,n_2], -n/2 \le n_1,n_2 < n/2. \tag{8}$$
2. For each scale j and angle l, form the product
   $$\widetilde{U}_{j,l}[n_1,n_2]\hat{f}[n_1,n_2] \tag{9}$$
   wrap this product around the origin and obtain
   $$\tilde{f}_{j,l}[n_1,n_2] = W\left(\widetilde{U}_{j,l}\hat{f}\right)[n_1,n_2] \tag{10}$$
   where the range for n_1 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$ for (θ in the range $(-\pi/4\,,\pi/4)$)
3. Apply the inverse 2D FFT to each $\tilde{f}_{j,l}$, hence collecting the discrete coefficients $C^D(j,l,k)$.

III. PROPOSED METHOD

Pre- processing is applied to eliminate the noises in the retinal image. Noises may arise, due to the digitization process. Moreover, regarding the acquisition process, retinal images have often low contrast that cause to hardly detect the blood vessels. The aim of our method is to improve the image dynamic range to prepare images for next step, detection the blood vessels, and attain to higher accuracy and precision of segmentation.

Concerning our purpose, contrast enhancement, the green channel of colored retinal images is used, because compare to

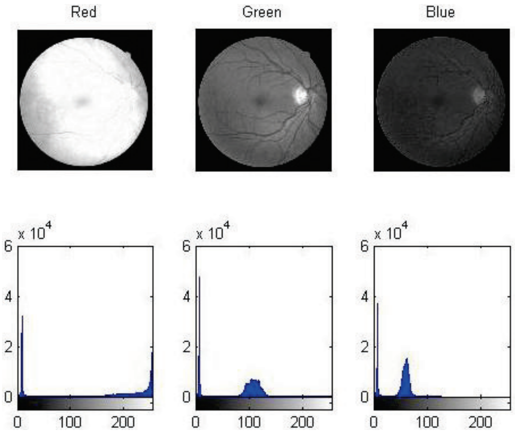

Fig. 2. Red, green and blue channels image and their corresponding histograms.

other channels it has the highest contrast. In fig. 2 the histogram of three channels are compared. Combining advantages of brightness in red channel decreasing the contrast between the abnormalities and the retinal background [17]; this helps to reduce some responses from abnormalities which do not resemble any blood vessels that would otherwise decrease the performance of blood vessels segmentation methods. For very bright images using the histogram of the red channel to modify that of the green channel decreases the contrast between retinal blood vessels and their background. This leads to a histogram matched image with contrast much lower than the contrast in the green channel image. In this case, the use of histogram matched images is preferred over the use of histogram matched images. To overcome this problem we used a condition to indicate when to apply the histogram matching. The condition to use green channel of an image is $C_{\mu_r} \geq 0.3$

$$\mu_r = \sum_{j=0}^{L-1} r_j P_r(r_j) \quad , \quad C_k = \sum_{j=0}^{k} P_r(r_j) \tag{11}$$

$P_r(r)$ is the probability density function for the red channel image, k is the bin containing the mean value μ_r, and L is the number of discrete gray-levels [18].

Since the Curvelet transform is well-adapted to represent the images containing edges, it is a good candidate for edge enhancement. Curvelet coefficients can be modified in order to enhance the edges in an image. To this end, we use the function introduced in [19] for wavelet transform because we want to modify the representation coefficients in such a way that details of small amplitude are enlarged at the expense of the ones with larger amplitude and perform this uniformly over all scales. Therefore, there is a need to a nonlinear function such as y to multiply against the transform coefficients. The function defined as below

Fig. 3. Enhancement map for $p = 0.5, C = 3, M = 50$

$$y(x) = \begin{cases} \left(\frac{m}{c}\right)^p & if \quad |x| < c \\ \left(\frac{m}{|x|}\right)^p & if \quad c \leq |x| < m \\ 1 & if \quad |x| \geq m \end{cases} \tag{12}$$

here, $0 < p < 1$ determines the degree of nonlinearity and c is a cross-over parameter: for values larger than c the modification is nonlinear, for values smaller than c the modification is linear (multiplication with a constant). This is done to prevent unnecessary over-enhancement of the noise in the image. The value of c should therefore be related to the noise content of the image, e.g. we can take c to be the estimated standard deviation of the noise in the image [19]. Multiplying each coefficient by corresponding y obtains the modified coefficients. In order to use introduced functions we manipulate the function parameters to adapt the functions better to our experience. Parameters c and m are defined according to two statistic features of coefficients. The first one is noise standard deviation, with the aim of preventing the noise amplification and the second one is maximum value of coefficients in each band. We choose $c = \sigma_{ji}$ where σ_{ji} noise standard deviation of coefficients being in the same direction and same scale. And $m = k(M_{ij} - \sigma_{ji})$ where M_{ij} is the maximum value of coefficients being in the same scale and same direction and k is an additional parameter. The advantage is that k is now independent of the Curvelet coefficient values, and therefore much easier for a user to set. Consequently, our proposed method consists of following steps:

1) Choose the green channel image form given colored

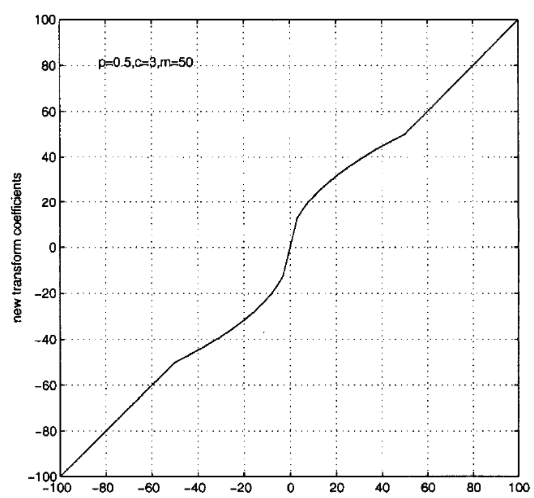

image.
2) Histogram matching if needed (regarding to parameter C_{μ_r}).
3) Applying FDCT via wrapping method. We get a set of scales S_j, each scale consist of a set of directional bands D_i containing coefficients.
4) For each directional band in each scale D_{ji} do the following:
   a. Calculate the noise standard deviation σ_{ij} .
   b. Calculate the Maximum value of the D_{ji} .
5) Multiply each coefficient individually by corresponding y.
6) Reconstruct the enhanced image using modified Curvelet coefficients.

IV. Experiments and Results

A. Databases

The images are used in this paper belong to a publicly available database, is known as DRIVE [20]. It consists of 40 images (seven with pathologies) captured by a Canon CR5 3CCD camera with a 45 FOV. The FOV is circular with approximately 540 pixels in diameter. For each image, a mask image is provided that delineates the FOV. Hence, detection of the FOV border is not needed in this case. The images are compressed in JPEG format and are divided into a training set and a test set, each containing 20 images. The test set has four images with pathology. The training set is useful to design supervised segmentation methods. All the images were manually segmented. Those of the test set were segmented twice, resulting in a set A and a set B. In set A, 12.7% of pixels were marked as vessel, against 12.3% for set B. Performance is evaluated on the test set using the segmentations of set A as ground truth [3].

B. Experimental results

Image enhancement quality is difficult to assess. Considerable literature exists relative to image quality estimation [21,22]. Therefore, our proposed method was applied and the results were compared to previous methods result visually.

As mentioned above, the green channel image in the database was considered to apply Curvelet transform. In order to apply FDCT via wrapping 5 scales and 16 directions in the coarse scale were considered that cause 32 directions in scales 2nd and 3rd, and 64 directions in scales 4th and 5th. Using the modification in function parameters explained above, and applying to each coefficient, the modified coefficients were produced and in last the inverse Curvelet transform was applied to get the enhanced image.

Fig. 4 shows the comparison between our and other methods result. Peng Feng *et al.* [14] compared their method with other methods and mentioned the weakness and strength of each method and we mention them here briefly. Histogram equalization appears to have good results but with some disadvantages such as: the absence of some grey levels, nonuniform background, amplification of noise and making parts of vessels invisible especially in much brighter backgrounds. Local normalization amplifies the noise strongly. In the image related to unsharp masking, the background noise is high and gray distribution is not uniform. The wavelet method result is inferior to Contourlet because of the nonuniform background which affects segmentation procedure. The anisotropy scaling law and directionality is critical for the Contourlet transform to keep the thin vessels and nerves undistorted during the decomposition and

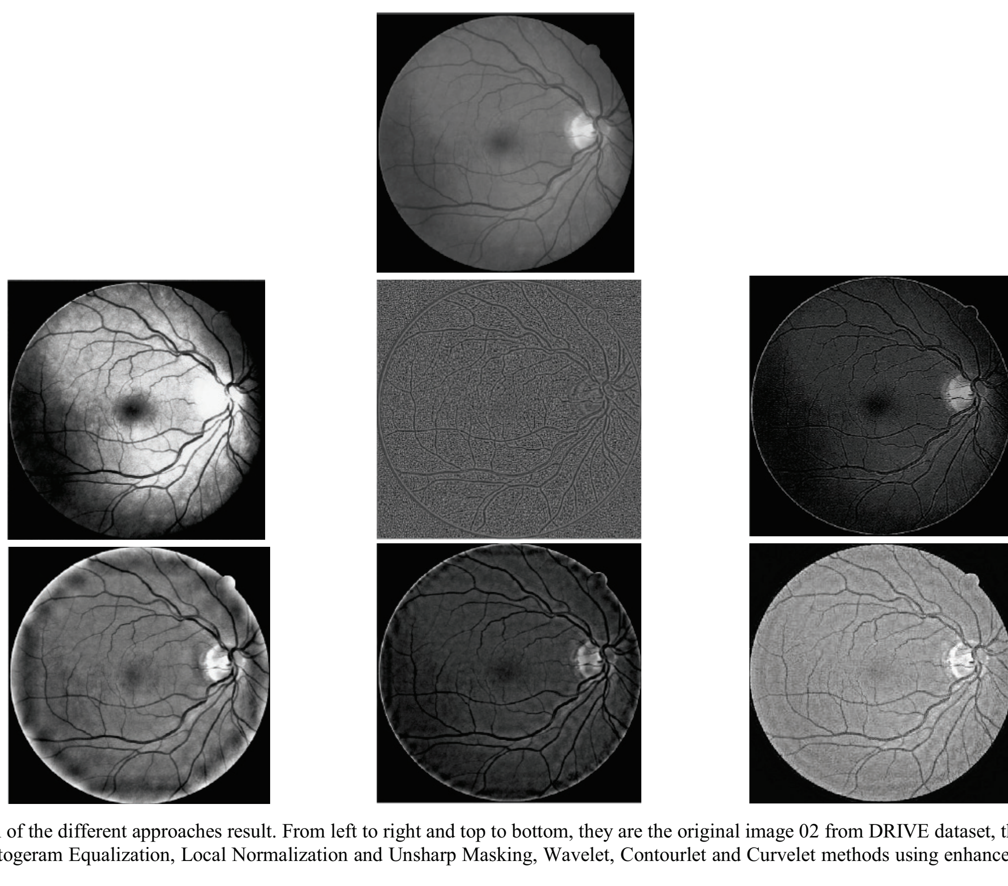

Fig. 4. Comparison of the different approaches result. From left to right and top to bottom, they are the original image 02 from DRIVE dataset, the corresponding green channel, Histogeram Equalization, Local Normalization and Unsharp Masking, Wavelet, Contourlet and Curvelet methods using enhancement function y_c and y respectively.

reconstruction and represent the image more sparsely than the wavelet transform. Since Contourlet and Curvelet both benefit from these two geometrical features they are both suitable for image enhancement. All disadvantages mentioned affect the image segmentation which is the next expected step. It is obvious that applying Curvelet transform improved the image contrast. Some unrecognized thin vessels became easy recognizable and as we mentioned before, using statistic features of coefficients in enhancement function allows us to make the function more adaptive to input image which changes its parameters concerning to input image. Also, it helps us in dealing with noise and prevents to amplify noise, which makes other approach inferior. Another superiority of our method is the uniform background, while the contrast between vessels and background increased; the illumination of the whole image improved and became better than Contourlet transform.

Therefore, considering discussed factors which affect the next step - blood vessel segmentation - our method promisingly enhanced the image contrast and is helpful to improve performance of blood vessel detection.

V. Conclusion

In this paper a method for retinal image contrast enhancement was presented by modifying the Curvelet coefficients. Curvelet transform is suitable for image enhancement as it represents the edges better than other multi-resolution methods. Therefore, the Curvelet coefficients were modified with the aim of enhancement of image contrast and preventing the amplification of the noise, simultaneously. We believe that applying such pre-processing procedure can be helpful for applications such as image segmentation.

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