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Contrast Enhancement in Retinal Image via Multi-Scale Geometrical Analysis

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Abstract: We present in this study, a new Multi-scale Geometrical Analysis method for ophthalmic image contrast enhancement based on the contourlet transform. The contourlet transform has better performace in representing edges than wavelets due to its anisotropy and directionality and is therefore, well-suited for multiscale edge enhancement. We modify the contourlet coefficients in corresponding subband and take the noise into account for more precisely reconstruction and better visualization. We compare this approach with enhancement based on the curvelet transform, and the traditional Histogram Stretching (HS). Our findings are that contourlet based enhancement out-performs other enhancement methods on low contrast and dynamic range images and can clearly identify the vessels and nerves in ophthalmic image.

Key words: Contourlet transform, contrast enhancement, curvelet transform, Multi-scale Geometric Analysis (MGA)

INTRODUCTION

Recently, there has been a growing awareness to the observation that wavelets may not be the best choice for representing natural images. This observation is due to the fact that wavelets are blind to the smoothness along the edges commonly found in images. In other words, wavelet can't provide the 'sparse' representation for an image because of the intrinsic limitation of wavelet. Hence, recently, some new transforms have been introduced to take advantage of this property. The curvelet (Candes and Donoho, 1999) and contourlet transform (Do and Vetteru, 2005) are examples of two new transforms with a similar structure, which are developed to sparsely represent natural images. Both of these geometrical transforms offer the two important features of anisotropy scaling law and directionality and therefore are good candidate for edges enhancement. Do and Vetterli (2005) utilized a double filter banks structure to develop the contourlet transform and used it for some non-linear approximation and de-noising experiments. In this research, we propose a new approach for medical image contrast enhancement, especially for ophthalmic image, that is based on an optimized contourlet transform. As we all know, numerous optic nerves and capillary vessels are in eyes and are difficult to distinguish in the ophthalmic image because of its low gray contrast and dynamic range. So it is very important to enhance the contrast of these images as well as keep the slim nerves and vessels undistorted. We compare this approach with enhancement based on Histogram Stretching (HS), Curvelet transform. Our simulation results show significant improvements and achieve better visual results and outperformed the previous methods.

CONTRAST ENHANCEMENT

The contourlet transform: Figure 1 shows a flow graph of the contourlet transform. It consists of two steps: the subbands decomposition and the directional transform. Laplacian Pyramid (LP) is first used to capture the point discontinuities, then followed by a Directional Filter Bank (DFB) to link point discontinuity into linear structure. The overall result is an image expansion using basic elements like contour segments, and thus named contourlet. Figure 2 shows an example of the frequency decomposition achieved by the DFB. Quincunx filter banks are the building blocks of the DFB. To decrease

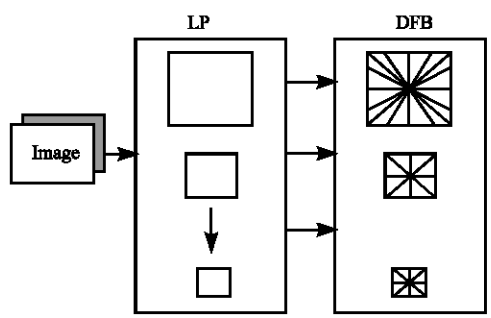

Fig. 1: A flow graph of the contourlet transform. The image is first decomposed into subands through Laplacian Pyramid and then each bandpass/detail image is analyzed by the directional filter banks

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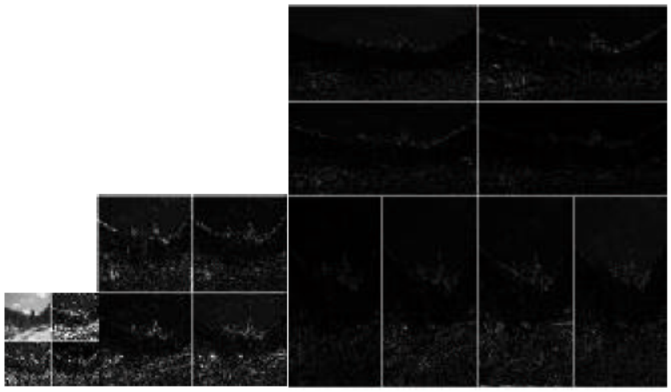

Fig. 2: Examples of the contourlet transform on the "Scene" images. For clear visualization, it is only decomposed into three pyramidal levels, which are the decomposed into four and eight directional subbands. Small coefficients are shown in black while large coefficients are shown in white

artifacts due to the Gibbs-like phenomenon in the DFB stage, we move downsampling and resampling to the end of the synthesis part and to the beginning of the analysis part, using the Nobel identities. Figure 2 depicts the contourlet coefficients of the Scene image using 3 LP levels and 8 directions at the finest level.

Image contrast enhancement: Since the contourlet transform is well-adapted to represent images containing edges, it is a good candidate for edge enhancement. Contourlet coefficients can be modified in order to enhance edges in an image. A function y_α must be defined which modifies the values of the contourlet coefficients. Take the noise into account, here we introduce explicitly the noise standard deviation σ in the equation (Valde, 1999).

$$
\begin{aligned}
y_\alpha(x,\sigma) &= 1 \text{ if } x < \alpha\sigma \\
y_\alpha(x,\sigma) &= \frac{x-\alpha\sigma}{\alpha\sigma} \bullet \left(\frac{t}{\alpha\sigma}\right)^q + \frac{2\alpha\sigma - x}{\alpha\sigma} \text{ if } \sigma \le x < 2\alpha\sigma \\
y_\alpha(x,\sigma) &= \left(\frac{t}{x}\right)^q \text{ if} 2\alpha\sigma \le x < t \\
y_\alpha(x,\sigma) &= \left(\frac{t}{x}\right)^s \text{ if } x \ge t
\end{aligned} \tag{1}
$$

Here, t determines the degree of nonlinearity and s introduces dynamic range compression. Using a nonzero s will enhance the faintest edges and soften the strongest edges at the same time. α is a normalization parameter. The t parameter is the value under which coefficients are amplified. This value depends obviously on the pixel value. We can derive the t value from the data. Two options are possible:

- $t = F_t\,\sigma$, where σ is standard noise deviation and F_t is an additional parameter which is independent of the contourlet coefficient values, and therefore much easier for a user to set. For instance, using $\alpha = 3$ and $F_t = 10$ amplifies all coefficients between 3 and 30.
- $t = lM_\alpha$, with $l < 1$, where M_α is the maximum contourlet coefficient of the relative band. In this case, choosing for instance $\alpha = 3$ and $l = 0.5$, we amplify all coefficients with an absolute value between 3σ and half the maximum absolute value of the band.

The first choice allows the user to define the coefficients to be amplified as a function of their signal to noise ratio, while the second one gives an easy and general way to fix m the parameter independently of the range of the pixel values. Figure 3 shows the curve representing the enhanced coefficients versus the original coefficients.

The contourlet enhancement method for grayscale images consists of the following steps:

- Estimate the noise standard deviation σ in the input image I.
- Calculate the contourlet transform of the input image. We get a set of subbands V_j, each band B_j contains N_j coefficients and corresponds to a given resolution level.
- Calculate the noise standard deviation σ_j for each b and j of the contourlet transform.
- For each band j do.
    - Calculate the maximum M_j of the band.
    - Multiply each contourlet coefficient $V_{j,k}$ by y_α $(|V_{j,k}|,\sigma_j)$.
- Reconstruct the enhanced image from the modified contourlet coefficients.

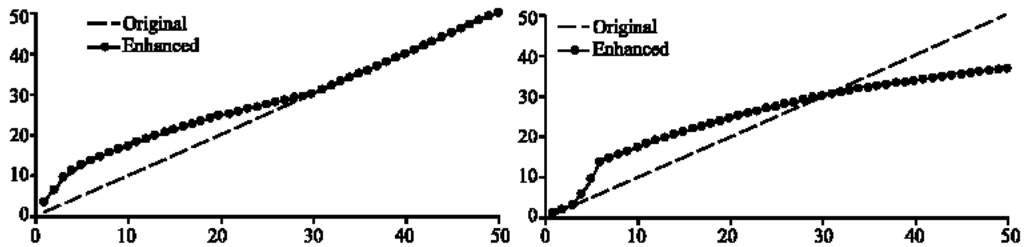

Fig. 3: Enhanced coefficients versus original coefficients; Parameters are Left: t = 30, α = 3, q = 0.5 and s = 0; Right: t = 30, α = 3, q = 0.5 and s = 0.6

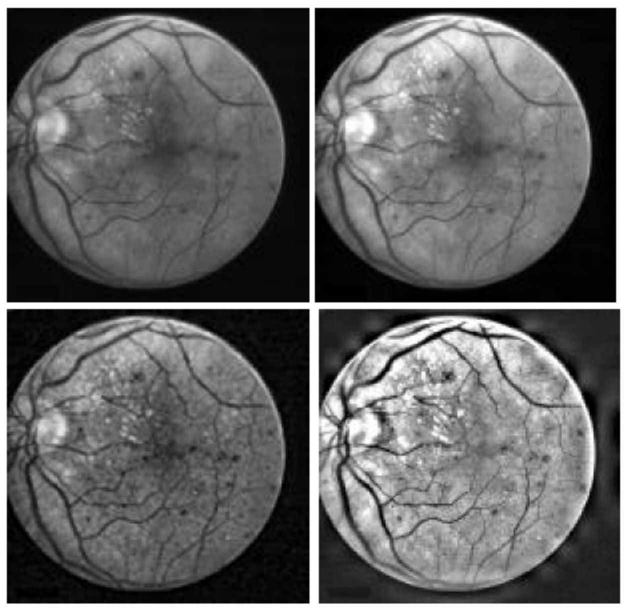

Fig. 4: Top: Original ophthalmic image and after histogram stretching. Bottom: enhanced image by the curvelet transform and the contourlet transform

NUMERICAL EXPERIMENTAL RESULTS

In order to test our algorithm, we used three approaches for our contrast enhancement experiments: the Histogram Stretching (HS), the curvelet transform in addition to the proposed contourlet transform. For the contourlet transform, we use 5 LP levels and 32 directions at the finest level. In the LP stage we choose the "9-7" filters partly because this bi-orthogonal filters is linear phase and are close to being orthogonal which is crucial for image processing. In the DFB stage we use the "23-45" bi-orthogonal quincunx filters designed by Phoong *et al*. (1995) and modulate them to obtain the bi-orthogonal fan filters. In particular, here we use curvelet transform with the same contrast enhancement method to compare with contourlet transform.

Figure 4 shows the results of, respectively, histogram stretching, the curvelet transform and the contourlet transform, using one image of eyeground which is downloaded from http://www-stat.stanford.edu/~jstarck. No noise was added to the eyeground image that means small levels of noise standard deviation needed to take into consideration. It's obviously the image contrast has been improved after contourlet transform approach. A few unrecognizable capillary vessels can be easily identified and the background of the image is brighter which is more comfortable and clear for visualization. And specifically, the curvelet transform was developed initially in the continuous-domain (Candes and Donoho, 1999) then require a rotation operation and correspond to a 2D frequency partition based on the polar coordinate. This not only causes the implementation for discrete images-

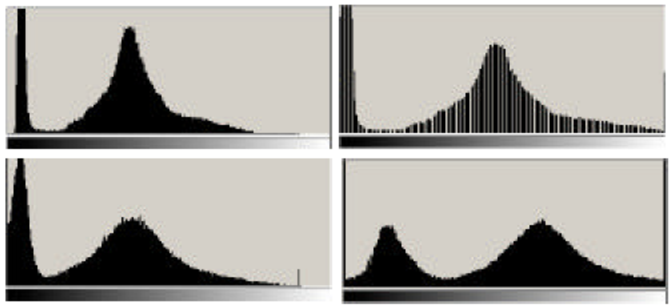

Fig. 5: Top: The histogram of original image and after Histogram Stretching. Bottom: The histogram of image enhanced by the curvelet transform and the contourlet transform

sampled on a rectangular grid-very challenging, but also brings some "Gibbs" like phenomenon or the block effect, in other words, the aliasing spectrum. But contourlet transform is defined in discrete domain directly which avoids the difficulty and aliasing spectrum. And this feature is critical for contourlet to keep the slim vessels and nerves undistorted during the decomposition and reconstruction.

Figure 5 shows the histogram of image before and after the proposed enhancement methods. The original histogram does not cover the whole gray scale (0-255). The image after HS (Histogram Stretching) loses some gray levels even though its distribution covers the whole range. Compared with the approach based on curvelet, the histogram of contourlet approach is smoother than curvelet based method and the center of the histogram of contourlet approach moves slightly toward 255, which means brighter image.

In summary, the results of these figures indicate that the contourlet based enhancement approach works well and bring some advantages for observation.

CONCLUSION

In this study, we study image contrast enhancement by modifying Contourlet coefficients. Experimental results show that this method gives better results than the approach based on curvelet transform and Histogram Stretching.

A number of properties, respected by the contourlet filtering described here, are important for contrast stretching.

- Reconstruct the enhanced image from the modified contourlet coefficients. Noise must be taken into consideration and not be amplified in enhancing edges.
- Reconstruct the enhanced image from the modified contourlet coefficients. It is very advantageous there is no block effects unlike curvelet and wavelet transform approach.

Then our conclusions are as follows:

- The contourlet and curvelet enhancement functions take account very well of image noise.
- As evidenced by the experiments with the contourlet transform, there is better detection of contours than with other methods.

For the low dynamic range and low contrast images, there is a large improvement by contourlet enhancement over other proposed approaches since the contourlet can detect the contours and edges quite adequately. But the enhancement function tends toward Velde's approach in such weak noise cases, so what we need to do in next step is to concentrate on the dependency of noise for this promising method.

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