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Enhancing retinal image by the Contourlet transform

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Abstract

The evaluation of retinal images is widely used to help doctors diagnose many diseases, such as diabetes or hypertension. Due to the acquisition process, retinal images often have low grey level contrast and dynamic range. This problem may seriously affect the diagnostic procedure and its results. Here we present a new multi-scale method for retinal image contrast enhancement based on the Contourlet transform. The Contourlet transform has better performance in representing edges than wavelets for its anisotropy and directionality, and is therefore well-suited for multi-scale edge enhancement. We modify the Contourlet coefficients in corresponding subbands via a nonlinear function and take the noise into account for more precise reconstruction and better visualization. We compare this approach with enhancement based on the Wavelet transform, Histogram Equalization, Local Normalization and Linear Unsharp Masking. The application of this method on images from the DRIVE database showed that the proposed approach outperforms other enhancement methods on low contrast and dynamic range images, with an encouraging improvement, and might be helpful for vessel segmentation.

Keywords: The Contourlet transform; Anisotropy and directionality; Contrast enhancement; Retinal imaging

1. Introduction

The evaluation of retinal images is a diagnostic tool widely used to gather important information about patient retinopathy. Retinal lesions, related both to vascular aspects, such as increased vessel tortuosity (Williams et al., 1999; Heneghan et al., 2002) or focal narrowing (Hubbard et al., 1999), and to nonvascular features, such as haemorrhages, exudates, microaneurysms and others (Ege et al., 2000), are crucial indicators of serious systemic diseases, such as diabetes or hypertension. It is thus very important for the doctors to be able to clearly detect, appreciate and recognize the lesions among the numerous capillary vessels and optic nerve present in the image. But the retinal images acquired with a fundus camera often have low grey level contrast and dynamic range. Fig. 1 is one example of such a retinal image. This problem may seriously affect the diagnostic procedure and its results, because lesions and vessels in some areas of the FOV are hardly visible to the eye specialist.

Obviously, contrast enhancement is a necessary pre-processing step if the original retinal image is not a good candidate for subsequent accurate segmentation. Several techniques have been used to improve the image quality. The classic one is Histogram Equalization (Zimmerman and Pizer, 1988) which has good performance for ordinary images, such as human portraits or natural images, but is not a good choice for ophthalmic images due to its amplification of noise and the absence of some grey levels after enhancement. More complex methods such as unsharp masking (Polesel et al., 1997; Yang et al., 2003) and a local normalization (Joes et al., 2004), have been proposed to enhance the contrast. The former, based on space filter, tries to add high frequency components of the image to

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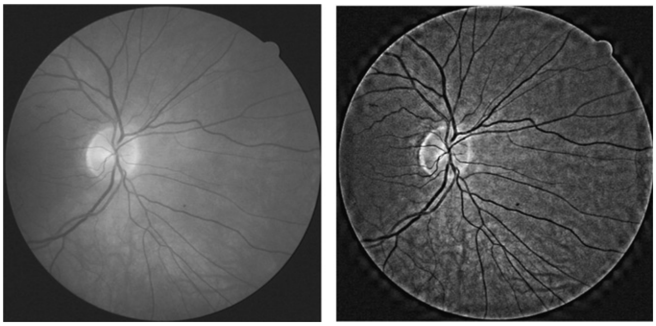

Fig. 1. Example of observed retinal image before and after enhancement.

the original image. The latter locally normalizes each pixel of the retinal image to zero mean and unit variance, aimed at compensating for the lighting variations and enhancing local contrast. It is clearly that both methods act as high-pass filters and, inevitably, augment the noise as well as improving the contrast. Others techniques based on matched filters have also been introduced (Chaudhuri et al., 1989; Hoover et al., 2000; Lin et al., 2003). These techniques are good at enhancing local contrast, especially for blood vessel, in a small area, but for the whole image, the computation becomes difficult due to needing many various matched filters.

Recently, the wavelet transform has been widely used in the medical image processing. Mallat (1989) introduced a fast discrete wavelet transform algorithm that is the method of choice in many applications. Laine and Song (1992,) and Laine et al. (1994) use this algorithm to enhance the microcalcifications in mammograms. Fu et al. (2000a,b) used a wavelet-based histogram equalization to enhance sonogram images. The wavelet transform is a type of multi-scale analysis that decomposes input signal into high frequency detail and low frequency approximation components at various resolutions. To enhance features, the selected detail wavelet coefficients are multiplied by an adaptive gain value. The image is then enhanced by reconstructing the processed wavelet coefficients. In our opinion, the wavelet transform may be not the best choice for the contrast enhancement of a retinal image. This observation is based on the fact that wavelets are blind to the smoothness along the edges commonly found in images. In other words, wavelet can not provide a 'sparse' representation for such an image because of the intrinsic limitation of wavelet. Some new transforms have been introduced to take advantage of this property. The Curvelet (Candès and Donoho, 1999) and Contourlet (Do and Vetterli, 2005) transforms are examples of two new transforms with a similar structure, which are developed to sparse represent natural images. Both of these geometrical transforms offer the two important features of an anisotropy scaling law and directionality and therefore are good choice for edge enhancement. Do and Vetterli (2005) utilized a double filter banks structure to develop the Contourlet transform and used it for some nonlinear approximation and de-noising experiments and obtained some encouraging results. In this work, a new approach for retinal image contrast enhancement that is based on Contourlet transform is proposed. The main reason for the choice of Contourlet is based on its better performance of representing edges and textures of natural images, i.e. better representation of lesions and blood vessels of a retinal image. We compare this approach with other contrast enhancement methods: Histogram Equalization (HE), the local normalization (LN) (Joes et al., 2004), linear unsharp masking (LUM) and the wavelet-based contrast enhancement in addition to the proposed Contourlet transform method. Our experimental results show encouraging improvement and achieve better visual results and outperformed the previous methods.

2. System architecture

Fig. 2 shows a flow chart for the proposed scheme. First, the retinal images captured from camera need to be transformed from RGB to greyscale. The histogram stretching is applied to the grey image for preliminary enhancement. Then Contourlet transform is applied. Here we do not use the histogram equalization as the first step although it is more effective. Ideally, histogram equalization should enhance the image contrast by adjusting the pixel distribution so that they can conform to an uniform distribution. However, this method will lose lots of information which maybe very important for lesion or vessel detection due to its absence of some grey-level after processing.

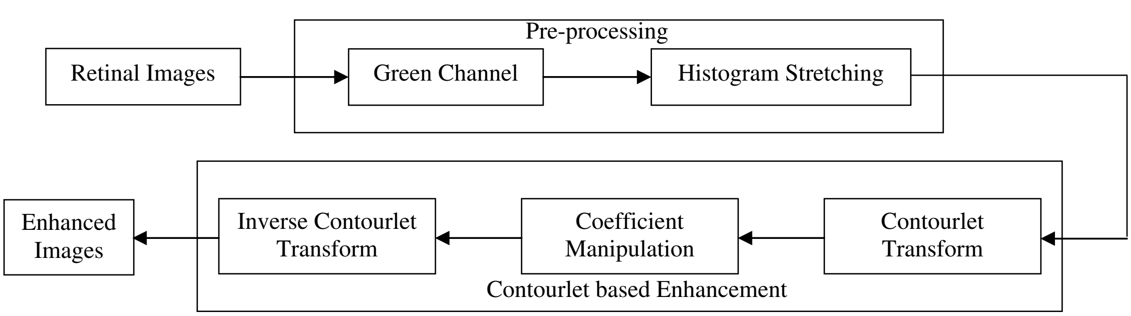

Fig. 2. Diagram for the proposed scheme.

2.1. Retinal image database

Most of our test images are taken from a standard retinal image source—the Utrecht DRIVE database.[1] It was obtained from a screening program in the Netherlands. All the retinal images are captured in digital form from a Canon CR5 nonmydriatic 3CCD camera at 45° field of view. The images are of size 768×584 pixels, 8 bits per colour channel and have a field of view (FOV) of approximately 540 pixels in diameter. Because the green channel of colour retinal images formatted as an RGB image gives the highest contrast between vessels and background, this channel is a good choice for contrast enhancement. We first extract the green channel of retinal images. Fig. 3 shows the each channel of an RGB retinal image and their histograms, respectively. It is easily to show that red and blue channels are either too bright or too dark.

2.2. The Contourlet transform

Fig. 4(a) shows a flow graph of the Contourlet transform. It consists of two steps: the subbands decomposition and the directional transform. A Laplacian pyramid (LP) is first used to capture 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 is thus named the Contourlet. Fig. 4(b) shows an example of the frequency decomposition achieved by the DFB. It depicts the Contourlet coefficients of one retinal image using three LP levels and eight directions at the finest level. Quincunx filter banks are the building blocks of the DFB.

2.3. Image contrast enhancement

If background has similar grey level with object, the details of this object is hard to detect. So if the wide blood vessels in retinal image which represent as strong edges are easy to find, the thin lesions and nerves are hard to detect due to their similar grey levels to the background. The proposed strategy softens the strongest edges and amplifies the faint edges. We try to reduce the ratio of strong features to faint features so that the slim vessels become visible.

Since the Contourlet transform is well-adapted to represent images containing edges, it is a good candidate for microstructure enhancement in retinal images as well as edge enhancement in natural images. Contourlet coefficients can be modified via a nonlinear function y_α. Taking noise into consideration, we introduce explicitly a noise standard deviation σ in the equation (Velde, 1999; Starck et al., 2003)

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

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

(1) $t = F_t\sigma$, 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.
(2) $t = lM_\alpha$, 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 t independently of the range of the pixel values. Fig. 5 shows a plot representing the enhanced coefficients versus the original coefficients.

The Contourlet enhancement method for green channel images consists of the following steps:

Step 1. Input the colour retinal image and extract its green channel.
Step 2. Apply histogram stretching to the grey retinal image.
Step 3. Estimate the noise standard deviation σ in the input image I (Starck et al., 2002).
Step 4. Calculate the Contourlet transform of the input image (Do and Vetterli, 2005). We get a set of subbands V_j, each band V_j contains N_j coefficients $C_{j,k}$ ($k \in [1, N_j]$) and corresponds to a given resolution level.
Step 5. Calculate the noise standard deviation σ_j for each band j of the Contourlet transform.
Step 6. For each band V_j do
  (1) Calculate the maximum value M_j of the band.
  (2) Multiply each Contourlet coefficient $C_{j,k}$ by $y_\alpha(|C_{j,k}|, \sigma_j)$.
Step 7. Reconstruct the enhanced image from the modified Contourlet coefficients.

[1] The images are available at: http://www.isi.uu.nl/Research/Databases/DRIVE/.

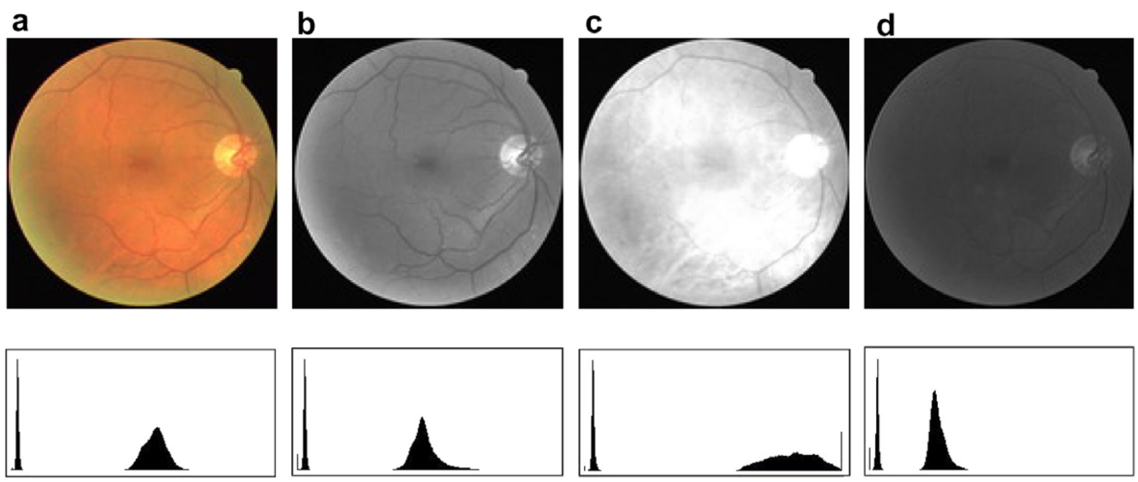

Fig. 3. Top: The original colour retinal image and its component of each channel, bottom: corresponding histogram of the four images. (a) Original image, (b) green channel, (c) red channel, (d) blue channel. (For interpretation of the references in colour in this figure legend, the reader is referred to the web version of this article.)

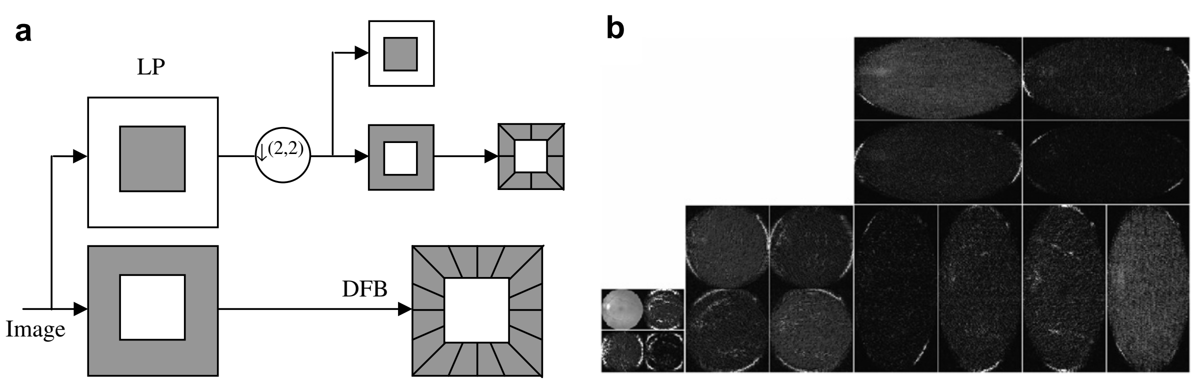

Fig. 4. (a) A flow graph of the Contourlet transform. The image is first decomposed into subbands through Laplacian Pyramid and then each bandpass/detail image is analyzed by the directional filter banks. (b) Examples of the Contourlet transform on one retinal image. For clear visualization, it is only 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.

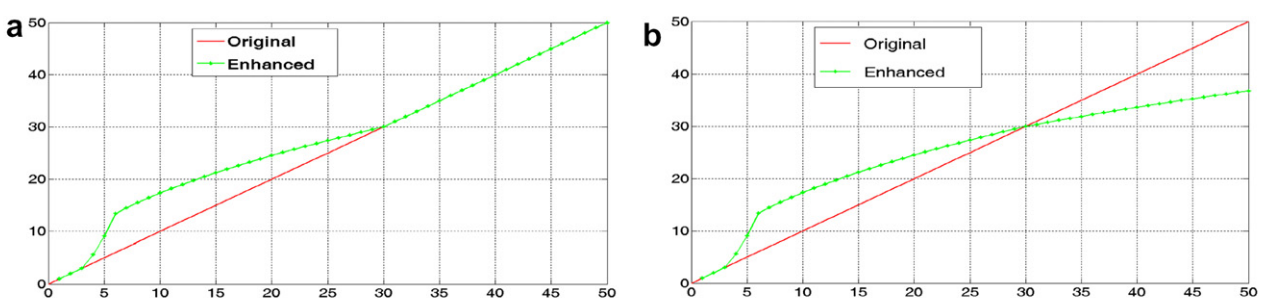

Fig. 5. Enhanced coefficients versus original coefficients; parameters are (a) $t = 30$, $\alpha = 3$, $q = 0.5$ and $s = 0$; (b) $t = 30$, $\alpha = 3$, $q = 0.5$ and $s = 0.6$.

3. Experiments and evaluation

In order to better appreciate the results obtained with our proposed algorithm, we used four approaches for our contrast enhancement experiments: Histogram Equalization (HE), local normalization (LN) (Joes et al., 2004), linear unsharp masking (LUM) and the wavelet-based contrast enhancement in addition to the proposed Contourlet transform. Most of our test images are from the standard retinal image source-DRIVE database. Using the green channel and the central part of the test image which is a 540×540 square (it covers the FOV area), we carried out all the experiments. For the Contourlet transform, we use five LP levels and 32 directions at the finest level. In the LP stage we chose the "9–7" filters partly because these bi-orthogonal filters have linear phase 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 modulated them to obtain the bi-orthogonal fan filters. In particular, here we use the wavelet transform with the same contrast enhancement function to compare with the Contourlet transform. The wavelet transform uses Daubechies bi-orthogonal 9–7 wavelet and a four level decomposition.

Fig. 6 shows one example of the results of histogram equalization, the local normalization, linear unsharp masking, wavelet-based and Contourlet-based enhancement. It is clear that the image contrast has been improved after Contourlet transform approach. A few unrecognizable capillary vessels can be easily identified. And specifically, due to the introduction of noise standard deviation in the enhancement equation, it is superior to HE and LN in

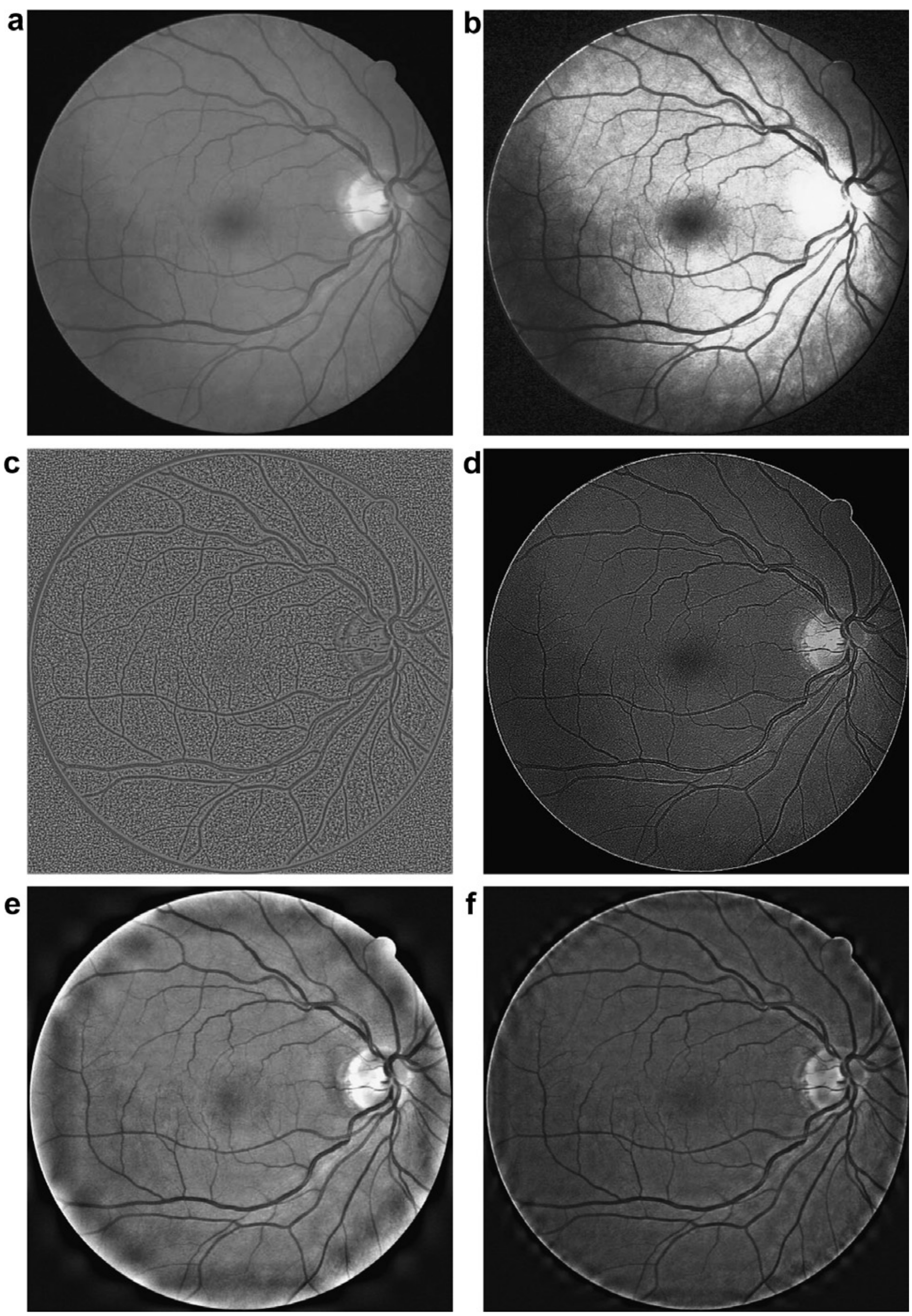

Fig. 6. Results on an image from DRIVE database with different enhancement approaches: (a) original image, (b) histogram equalization (HE), (c) local normalization (LN), (d) linear unsharp masking (LUM), (e) wavelet, (f) Contourlet.

the sense that it does not strongly amplify the high frequency part of the whole image, i.e. noise. The uniform background distribution is also helpful for results because we do not amplify the low-amplitude coefficients.

It appears that histogram equalization has better performance in the experiments. Unfortunately some intrinsic disadvantages also exist: the absence of some grey levels and nonuniform background/luminosity distribution. The drawback is easy to find: parts of the vessels become invisible for the too bright background. Another disadvantage is well-known: histogram equalization strongly amplifies the noise. This feature will make the next step-vessel segmentation-hard to complete and even destroy the vessel or lesion. Local normalization which aims at normalizing each pixel of the image to zero mean and unit variance also amplifies the noise strongly. Although the edges, blood vessels and nerves of the retinal image are easy to identify, the noise is too great. With carefully choosing the parameters of linear unsharp masking, we get a better result compared with histogram equalization and local normalization, but the background grey distribution is not uniform and unsharp masking results in more noise in the background.

Fig. 6(e) and (f) shows the comparison of wavelet and Contourlet transform enhancement with the same enhancement function. Both of two transform-based approaches improve the contrast of retinal image and have the artifacts due to the same reason: shift-variance. It seems that the wavelet is inferior to Contourlet in the sense that (b) has the higher contrast between vessels and background than (a) does, we still can see some faint and thin vessels which are almost invisible in (a). As mentioned in introduction, the anisotropy scaling law and directionality is critical for the Contourlet transform to keep the thin vessels and nerves undistorted during the decomposition and reconstruction and represent the image more sparsely than the wavelet transform.

In summary, the results of these figures indicate that the Contourlet-based enhancement approach works well and bring some advantages. A worry for the proposed scheme is that the widths of some vessels are changed slightly. This phenomenon is partial because the Contourlet transform is not shift-invariant. It uses a 2×2 down-sampling after a Laplacian pyramid (LP) transform which will inevitably affect the reconstructed image after a manipulation of coefficients. That is why there are some artifacts outside the FOV, especially for the area where the grey level distribution has an obvious quickly change. Another problem is how to choose the appropriate parameters in our algorithm, the relationship between the statistical property of retinal image and the parameters of enhancement function need further investigation. Future visual evaluation and quantitative assessment will be the aim of future work.

4. Conclusion

In this paper, we studied image contrast enhancement by modifying Contourlet coefficients. Experimental results show that this method provides an effective and promising approach for retinal image enhancement.

A number of properties, are important for contrast stretching.

- Reconstructing the enhanced image from the modified Contourlet coefficients. Noise must be taken into consideration and not be amplified in enhancing edges.
- Reconstructing the enhanced image from the modified Contourlet coefficients. It is very advantageous there is no block effect.

Then our conclusions are as follows:

1. The Contourlet enhancement functions need take account very well of image noise.
2. As evidenced by the experiments with the Contourlet transform, there is better preservation of contours than with other methods.
3. The effect of shift-variance of Contourlet transform need further investigation in order to get more precise enhancement retinal image.
4. Careful research about the relationship between image statistical properties and the parameters of enhancement function should be applied in the future.

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. The enhancement function tends to changes the width of blood vessels, so what we need to do in next step is to concentrate on the effect of shift-variance of Contourlet transform and find the best appropriate parameters for this promising method.

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