Color Image Denoising and Contrast Enhancement in Contourlet Domain

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Abstract- A degraded image mainly has dark shadows, over bright regions and blurred details. These images are usually affected by noise. This paper proposes a method which tries to avoid these problems. Image denoising using hard thresholding method is first examined. The denoised image is further treated by a uniquely designed new transfer function. It is used to treat the contourlet transform coefficients. The contourlet transform is a directional extension of wavelet transform thus its application has a profound effect in image enhancement applications. The results found are encouraging. All important features of the image are kept with out introducing artifacts and color distortion. The results look more natural.

Key words: Image enhancement, thresholding, contourlet Transform, Wavelet Transform, transformation function.

I. INTRODUCTION

There exist several ways to represent a signal and the efficiency of a given representation depends on the subsequent processing. Different representations emphasize different aspects of a signal and therefore, one should look for representations that make relevant information easily accessible.

In the last two decades, multiresolution representations occupy an important role and have proved to be a powerful tool both theoretically and practically. Recent developments in multiresolution representation approaches include wavelet, ridgelet, curvelet and contourlet transforms. Most researchers indicate that directionality is a crucial feature in image representation; so we have picked the contourlet transform as our major image decomposition method [1, 2 3].

Image denoising and enhancement are the two areas where multiresolution is frequently used. It is used to reduce the noise level of a degraded image while sharpening details of the image itself. The basic idea of Multiresolution based image denoising and enhancement is as follows. Main signal components and noise possess distinct properties in the transform domain. The detail coefficients in each level of the multiresolution representation are passed through a specifically designed thresholding function where small values, which are likely to contain the noise, are set to zero, while larger values which include the main signal features are retained. The final enhanced image is obtained by performing inverse transformation process on the modified coefficients. Image denoising and enhancement are the main topics of this paper thus it is discussed in more details below.

Several literatures can be found in the ideas of multiresolution based image denoising and enhancement. The multisicale retinex (MSR) is the first to introduce the concept of multiresolution for contrast enhancement [4]. MSR softens the strongest edges and keeps the faint edges almost untouched. The opposite approach was proposed by Koen Vande Velde, 1999 [5] using the wavelet transform for enhancing the faintest edges and keeping untouched the strongest.

Another paper proposed by Xuil Zong et al, 1996 [6] presents an approach which addresses both de-noising and contrast enhancement using the multiresolution approach in the discrete wavelet transform (DWT) domain. Starck et al [7] used to the curvelet transform to enhancement still images and they claimed that the performance of their method is superb.

The subsequent parts of this paper are divided as follows. Section two presents a brief introduction of the contourlet transform. Section three discusses the algorithm. In section four the discussion and results part are presented and finally section five gives concluding remarks.

II. CONTOURLET TRANSFORM

In a nutshell the contourlet transform is an efficient directional multireslotuion expansion which is digital friendly. It is constructed via filter banks and can be viewed as an extension of wavelets with directionality. They inherit the rich wavelet theory and algorithms.

The proposed computational frame work of contourlets consists of multiscale decomposition followed by directional filter banks. The multiscale step captures a point discontinuity which is done by the Laplacian pyramid. The directional decomposition step links point discontinuities into linear structures. For rigorous discussion about contourlets the reader can refer to [1, 2, and 3].

Given an orthogonal basis $\left\{\phi_{j,n}\right\}_{n\in Z^2}$, where

$$\phi_{j,n}(t) = 2^{-j}\phi\left(2^{-j}t - n\right) \quad\dots\dots\dots\dots\dots\dots(1)$$

And a tight frame, $\left\{\mu_{j-1,n}\right\}_{n\in Z^2}$, where

$$\mu_{j-1,2n+k_i} = \varphi_{j,n}^{(i)}, \quad i = 0,\dots,3 \quad\dots\dots\dots\dots(2)$$

The directional multiresolution analysis for scale j, level l with k directions is:

$$\rho_{j,k,n}^{(l)}(t) = \sum_{m\in Z^2} g_k^{(l)}\left[m - s_k^{(l)}n\right]\mu_{j-1,m}(t) = \rho_{j,k}^{(l)}\left(t - 2^{j-1}s_k^{(l)}n\right)$$

$$\dots\dots\dots(3)$$

Where $n \in Z^2$, the first part of equation 3 is for directional filter bank basis and the second part for the Laplacian pyramid frame. This equation can be analyzed by filter banks as shown in Figure 1.
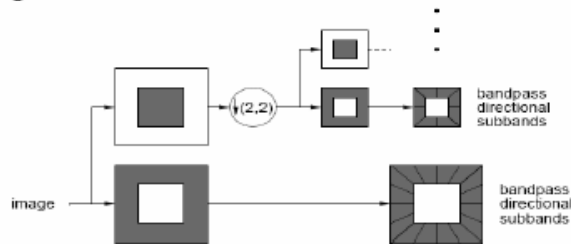

Fig. 1. Contourlet Filter bank

II. ALGORITHM

The algorithm in this paper consists of two major steps. The first step is multiresolution based denoising and the second step is multiresolution based image enhancement.

The general contourlet denosing procedure is as follows. First apply contourlet transform to the noisy signal to produce the noisy contourlet coefficients to the level which we can properly distinguish the all the image properties, in this case level 4 decomposition is optimum. Then Select appropriate threshold limit at each level and using a hard thresholding to best remove the noises [8].

Hard thresholding method is very popular in image denoising. It can preserve image details in some extent and be written as:

$$D(x,T) = \begin{cases} x, & |x| \geq T \\ 0, & |x| < T \end{cases} \quad\dots\dots\dots\dots\dots\dots(4)$$

Where T is a threshold which is dependent on the Gaussian white noise of variance σ^2. To accurately calculate the variance of a noisy image is usually a difficult task, but we can effectively estimate it by using a robust mean estimator defined by:

$$\sigma = \frac{median(|c|)}{0.6745} \quad\dots\dots\dots\dots\dots\dots(5)$$

Where, c denotes the coefficients in multiscale contourlet decomposition of a given image.

According to the paper in [9], the thresholds of all directional subbands are calculated by:

$$T_{i,j} = 3\sigma_{i,j} \quad\dots\dots\dots\dots\dots\dots\dots\dots(6)$$

Where, i is the level index to the contourlet decomposition, j is the directional subband index in each level.

The second major step is to further analyze the denoised image using the proposed enhancement algorithm. This algorithm is based on the modification of contourlet coefficients. The developed algorithm is discussed thoroughly below. The performance of this method is evaluated using objective assessment methods as well as compared with other techniques.

Low visibility is generally presented in images as dark shadows, over bright regions and blurred details. All these are related to the luminance and contrast properties of images; therefore, it is a logical way to develop an image enhancement algorithm based on the processing of the luminance and contrast of an image.

For possible extension of the method in enhancement of general poorly-lit color images, it is always required transform the image into a color space which effectively decomposed the image into luminance and chrominance parts. From the paper Melkamu et al [10], the HSI (Hue, Saturation and Intensity) color model is found to be best suited for this purpose.

The image is first decomposed in to HSI components. The contourlet transform decomposes the intensity image into sub images based on the level of the specified decomposition. For each sub image, we compute the maximum magnitude coefficient value. Then each sub image is iteratively thresholded and the components are modified independently.

Let I represent the subband image

Define

$$x = \frac{aI}{\alpha m} \quad a = 1,\dots,2.5,\dots\dots\dots(7)$$

Where α is a threshold and m is maximum magnitude of the transformed subband image coefficient,

The enhancement function is then defined as:

$$f(x) = \frac{e^{2bx} - ce^{-x^2} + ce^{2bx-x^2} - 1}{e^{2bx} + 1} \quad\dots\dots\dots(8)$$

b and c are parameters which control the gain of the function. The range of b and c are determined empirically based on image enhancement experiments and authors' judgment. Coefficient values greater than αm are enhanced linearly with a gain of a.

Most multiresolution enhancement methods use transfer functions which are combined with to become continuous [5, 6, and 7]. This might sometimes change the position of the edges and the image will be deformed. The transformation function in equation 8 satisfies the following crucial conditions to perform the enhancement without introducing artificial artifacts.

1. The function is infinitely differentiable. This is a very important property which makes sure that the locations of the discontinuities remain unchanged after the enhancement has treated coefficients and no new edges will be created.
2. The function is nonlinear. Different parts of the image will be amplified with different gain. To enhance weak edges buried in the background, the enhancement function should be designed such that coefficients within the certain range are amplified with higher gain. This property of the function is shown below. Figure 2 clearly shows that the enhancement function elevates the values of low intensity pixels while higher values are untouched.
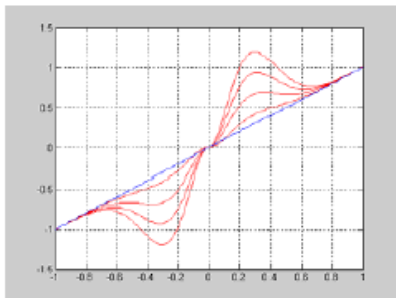

Fig. 2 Enhanced coefficients versus original coefficients with parameters a=1, b= 2, α=0.85, c=1, 2, 3, 4.

III. RESULTS AND DISCUSSION

This technique is tested in several test images. First we compare the denoising performance of the proposed contourlet transform with the wavelet transform, by using the same hard threshold denoising method discussed above. We implement 4 decomposition levels in both contourlet and wavelet transforms. And the number of directional decompositions in the contourlet transform is 16, 8, 4, and 3 at the scales from finer to coarser respectively.

Table1 shows the PSNR (in dB) of the denoised images by using the two transforms. It is evident that the proposed contourlet transform obtains better objective measure than wavelet in denoising application.

TABLE 1
COMPARISON OF THE DENOISING PERFORMANCE

σ	PSNR	
	Wavelet	Contourlet
10	32.44	33.01
20	31.91	32.35
30	30.02	30.99
40	28.42	29.41
50	27.11	27.20

Figure 3 shows comparison of the denoised "Barbara" image with original noise variance equal to 20.

Fig.3. Comparison of the denoising performance of the Barbara image (a) original image (b) noisy image, σ=20 (c) wavelet denoised (d) contourlet denoised

After the denoising step we perform the enhancement procedure. In this procedure the same experimental setup was followed as the denoising and it was tested in several test images. Figure shows a test image of taken at night.

The image in Figure 4 (a) shows a scene of a city. The image is taken in a low visible lighting condition. The image "suffers" from a low visibility. The color of the tree branches in the image appears to be dark but it is supposed to be green. Applying the enhancement system on this image gives a result which has a better clarity with no color distortion as shown in Figure 4(b). The result image has a good global contrast.

(a)　　　　　　　　　　　(b)

Fig. 4. Sample Enhancement result.

To assess the performance of our method we used an objective evaluation setup. Zhou Wang et al, 2004[11] proposed a new paradigm for quality assessment based on the hypothesis that the human visual system is highly adapted for extracting structural information. This measurement is called the structural similarity index measure (SSIM). We adopted this measure for our objective evaluation and the analysis for this method is given below.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad \ldots\ldots(9)$$

SSIM ranges from 0 to 1. Zero is for completely different images and 1 for perfect match. Results nearer to one are acceptable.

Image signals are non-stationary thus it is a good practice to measure over local regions rather than measuring through the entire image. In this case we propose a sliding window (w) approach. The window starts from the top-left corner of the images and ends at the bottom-right. Then the total index measure will be found by averaging the local measures. The window can have a size of *8X8*. The windowed structural similarity index measure is then given by:

$$WSSIM(x, y) = \frac{1}{|W|} \sum_{w \in W} SSIM(x, y|w) \quad \ldots\ldots\ldots(10)$$

Where W is the family of all windows and $|W|$ is the cardinality of W.

Figure 5(a) shows a chair and four binders on it taken using a digital camera in a room where the windows are opened and the light is turned on. This image serves as a reference image to measure the WSSIM and PSNR. Figure 5(b) is the same picture taken when the windows are closed and the light is turned off, still there is a little illumination but not enough to take a clear image. This is the image to be enhanced using different methods. Comparing results obtained when the test image is processed by histogram equalization (HE) (Figure 5(c)), Contrast limited adaptive histogram equalization (CLAHE) (Figure 5(d)), Wavelet (Figure 5(e)) and Contourlet

methods (Figure 5(f)); the contourlet method gives us a greater index and PNSR as shown in table 2.
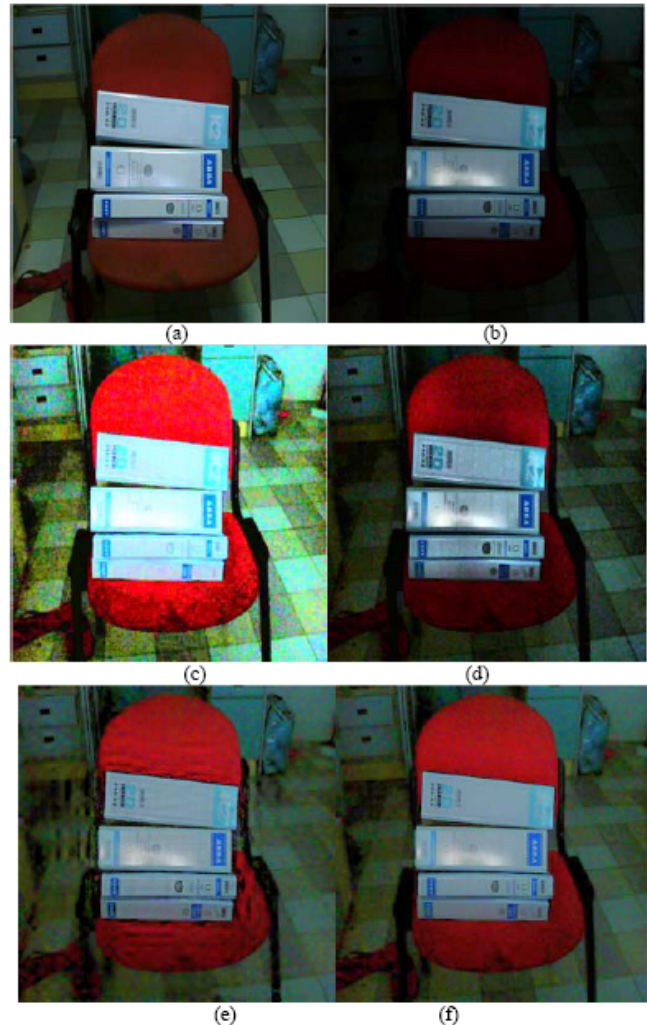

(a)　　　　　　　　　　　(b)

(c)　　　　　　　　　　　(d)

(e)　　　　　　　　　　　(f)

Fig. 5 Objective evaluation test image (a) Perfect reference image (b) test image(c) HE Method (d) CLAHE (e) wavelet enhanced image (f) contourlet enhanced image

This is obvious that the contourlet image has more brightness which is considerably different to that of the dark test image. The smooth shapes of the binders and the chair are maintained. HE and wavelet contain artifacts that are not originally in the image. Even though the HE method appears to be brighter; the color of the original image has considerably changed which is not wanted. In the CLAHE the enhanced image appears to be dark and its performance is inferior as compared with the contourlet method.

TABLE 2
OBJECTIVE PARAMETERS FOR THE ENHANCEMENT
PERFORMANCE COMPARISON

Method	WSSIM	PSNR
HE	0.9861	19.7333
CLAHE	0.9989	22.8724
Wavelet	0.9991	23.4461
Contourlet	0.9992	25.8193
Test image	0.3644	12.0913

IV. CONCLUSION

This approach is simple and effective. The denoising procedure can effectively remove the noise and the performance is very is better than the converntional wavelt tranfosrm. The enahcmeent proformance is also good as compared to other methods. The contourlet transform allows both global and local contrast enhancement with minimum distortion in image appearance. All the important features of the image are kept visible without introducing any artifacts. There is no color distortion in this method.

ACKNOWLEDGEMENT

REFERENCE

[1]. M. N. Do, M. Vetterli, J. Stoeckler and G. V. Welland, "Contourlets beyond wavelets" Academic Press, New York, 2002. Can be found in http://www.ifp.uiuc.edu/~minhdo/publications.

[2]. M.N. Do, M Veterli, "The Contourlet Transform: An efficient Directional Multi Resolution Image Representation", IEEE Transactions on Image Processing, 2005, Volume 14, Pages: 2091-2106.

[3]. Minh N. Do, "Contourlets and Sparse Image Expansions", SPIE 2003, Volume 5207, Page(s): 560-570.

[4]. Z. Rahman, D. J. Jobson, and G. A. Woodell, "Multi-scale retinex for color image enhancement," IEEE International Conference on Image Processing, 1996. Vol. 3, on Page(s): 1003-1006.

[5]. Koen Vande Velde, "Multi-scale Color Image Enhancement", IEEE Proceedings of International Conference on Image Processing (ICIP 99), 1999, Volume: 3, On page(s): 584-587.

[6]. Xuli Zong, A.F. Laine, E. A. Geiser, D.C. Wilson, "De-Noising and contrast enhancement via wavelet shrinkage and nonlinear adaptive gain" Proceedings of SPIE, in Wavelet Applications III, 1996. vol. 2762, on page(s): 566-574.

[7]. Jean-Luc Starck, Fionn Murtagh, Emmanuel J. Candès, and David L. Donoho, "Gray and Color Image Contrast Enhancement by the Curvelet Transform", IEEE Transactions on Image Processing, vol. 12, No 6, JUNE 2003, on page(s): 709-716.

[8]. Beibei Song, Luping Xu, Wenfang Sun, "Image Denoising Using Hybrid Contourlet and Bandelet Transforms" Fourth International Conference on Image and Graphics ,IEEE, on Page(s): 71-74.

[9]. Lu Y, Do M.N, "A new contourlet transform with sharp frequency localization", IEEE International Conference on Image Processing, 2006, on Page(s): 1629-1632.

[10]. Melkamu. H. Asmare ,Vijanth S. Asirvadam and Lila Iznita, "Color Space Selection for Color image Enhancement applicaitons", International Conference on Signal Aquisistion and processing (ICSCAP 2009), 3 - 5, April 2009, Kuala Lumpur, Malaysia, Page(s):352-356.

[11]. Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh, Eero P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity", IEEE Transaction on Image Processing, Volume 13, NO. 4, April 2004, Pages: 600-612.