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The Cycle Spinning-based Sharp Frequency Localized Contourlet Transform for Image Denoising

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Abstract

Contourlet transform provides flexible number of directions and captures the intrinsic geometrical structure of images. The efficient directional filter banks with low redundancy of contourlet are very attractive for image processing. However, non-ideal filters are used in the original contourlet transform, especially when combined with laplacian pyramid, which results in pseudo-Gibbs phenomena around singularities for image denoising. Sharp frequency localized contourlet transform (SFLCT) is a new construction contourlet to overcome this drawback by replacing the laplacian pyramid with a new multiscale decomposition which significantly improve the denoising performance than the original form. Unfortunately, the downsampling of SFLCT makes it lack translation invariance. Thus, we employ a cycle spinning (CS) method to improve the denoising performance of SFLCT, named as cycle spinning based SFLCT (CS-SFLCT), by averaging out the translation dependence. Experimental results demonstrate that the proposed CS-SFLCT outperforms SFLCT, contourlet and cycle spinning-based contourlet for denoising in terms of PSNR and in visual effects.

Keywords: denoising; cycle spinning; contourlet transform; wavelet transform; multiscale pyramid; directional filter banks; aliasing

1. Introduction

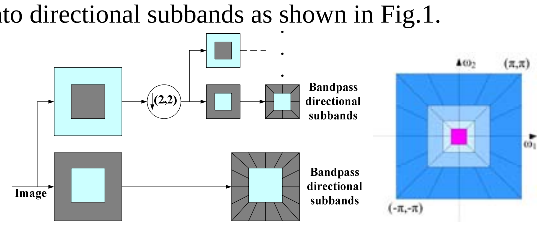
Images acquired by sensors are often abrupt by noise. Since the noise spreads over all the coefficients while image information concentrates on a few largest ones in the wavelet transform domain, wavelet becomes the most successful transform for denoising. However, traditional two dimension wavelet is hard to represent sharp image transitions [1] and smoothness along the contours [2]. Hence, bandelet [1] with adaptation to the geometric structure and contourlet [2] with anisotropy scaling law and directionality are presented to sparsely represent natural images. They both achieve better denoising performance than wavelet and also outperform wavelet in image fusion [3] [4]. However, the computation of geometry in bandelet is in high complexity thus it is not commonly used in other image processing tasks except image denoising, compression [1] and fusion [3].

Contourlet [2] proposed by Minh N. Do and Martin Vetterli is utilized to capture intrinsic geometrical structure and offer flexible multiscale and directional expansion form images. Because of the nearly critical sampling and fast iterated filter bank algorithm, contourlet is in lower complexity than bandelet. However, non-ideal filter are used in the original contourlet result in significant amount of aliasing components showing up at location far away from the desired support [5] and exhibit some fuzzy artifacts along the main image ridges. Yue Lu [5] proposes a new construction of the contourlet, called sharp frequency localization contourlet transform (SFLCT) and alleviates the non-localization problem even with the same redundancy of the original contourlet.

Unfortunately, due to the downsamplers and upsamplers presented in the directional filter banks of SFLCT, SFLCT is not shift-invariant, which is important in image denoising by thresholding and easily causes pseudo-Gibbs phenomena around singularities [6].In this paper, we apply cycle spinning [6] to compensate for the lack of translation invariance property of SFLCT and successfully employed in image denoising. Experimental results demonstrate that our proposed method outperforms the original contourlet (CT), SFLCT and cycle spinning-based contourlet (CS-CT) in terms of PSNR and visual effect.

2. Sharp Frequency Localized Contourlet Transform

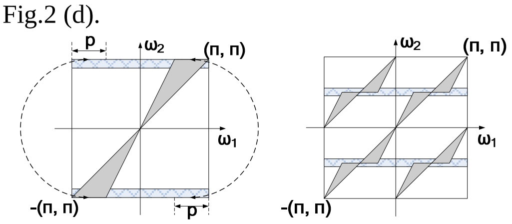
The original contourlet [2] is constructed by the combination of laplacian pyramid, which is first used to capture the point discontinuities, and the directional filter banks (DFB), which is used to link point discontinuities into linear structure. In the frequency domain, the laplacian pyramid iteratively decompose a two dimensional image into lowpass and highpass subbands and the DFB divide the highpass subbands into directional subbands as shown in Fig.1.



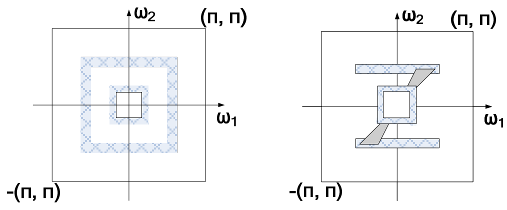
(a) (b)

Fig.1 The original contourlet transform. (a) Block diagram. (b) Resulting frequency division.

However, the frequency division in Fig.1 (b) is obtained by ideal filters. When non-ideal filters are combined with laplacian pyramid, and suppose only one direction is extracted, the aliasing frequency spectrum will concentrate along two parallel lines $\omega_2 = \pm\pi$ as shown in Fig.2 (a). Furthermore, if the directional filters are upsampled by 2 along each dimension, the aliasing components will be folded towards the lowpass regions, as patterned in Fig.2 (b), and concentrated mostly along two lines $\omega_2 = \pm\dfrac{\pi}{2}$. When the directional filters are combined with bandpass filter in laplacian pyramid, the contourlets are not localized in frequency, with substantial amount of aliasing components outside of the desired trapezoid-shaped support [5] as the gray region shown in Fig.2 (d).



(a) (b)



(c) (d)

Fig.2 Spectrum aliasing of the original contourlet. Gray regions represent the ideal passband support. Patterned regions represent the aliasing components or transition bands. (a) One directional filter, (b) The directional filter upsampled by 2, (c) A bandpass filter from the Laplacian pyramid, (d) The resulting contourlet subband.

To solve this problem, Yue Lu [5] proposes a new construction of a sharp frequency localization contourlet (SFLCT). Since the combination of laplacian pyramid and directional filters banks make the aliasing problem serious, new multiscale pyramid with different set of lowpass and highpass filters for the first level and all other levels are employed. Suppose lowpass filters $L_i(\boldsymbol{\omega})(i=0,1)$ in the frequency domain as $L_i(\boldsymbol{\omega}) = L_i^{1d}(\omega_1)\bullet L_i^{1d}(\omega_2)$ and $L_i^{1d}(\omega)$ is a 1-D lowpass filter with passband frequency $\omega_{p,i}$ and stopband frequency $\omega_{s,i}$ and a smooth transition band, defined as

$$L_i^{1d}(\omega)=\begin{cases}1 & \text{for } |\omega|\le\omega_{p,i}\\ \dfrac{1}{2}+\dfrac{1}{2}\cos\dfrac{(|\omega|-\omega_{p,i})\pi}{\omega_{s,i}-\omega_{p,i}} & \text{for } \omega_{p,i}<|\omega|<\omega_{s,i}\\ 0 & \text{for } \omega_{s,i}<|\omega|<\pi\end{cases}$$

for $|\omega|\le\pi$ and $(i=0,1)$.

Under the assumption that aliasing can be completely cancelled, the perfect reconstruction of multiscale pyramid should satisfy

$$|L_i(\omega)|^2+|D_i(\omega)|^2\equiv 1,\qquad \text{for}\quad i=0,1$$

Fig.3 shows the comparison on basis image of the original contourlet and SFLCT. Fig.3 (a) and (b) indicate that the frequency non-localization problem is serious in the original contourlet while this problem is suppressed by the new construction of contourlet. Furthermore, the spatial regularity of contourlet is greatly improved in SFLCT as shown in Fig.3 (c) and (d).

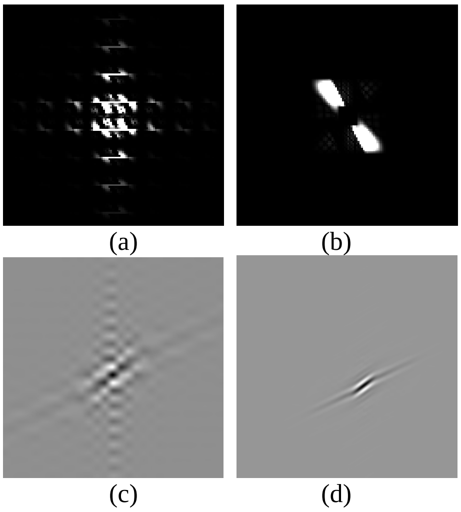


Fig.3 Basis images of original Contourlet and Sharp Frequency Localized Contourlet. (a) and (b) are basis images of original Contourlet and Sharp Frequency Localized Contourlet in frequency domain, (c) and (d) are basis images of the two transforms in spatial domain.

3. Image Denoising using Cycle Spinning-based Sharp Frequency Localized Contourlet Transform

Though SFLCT is sharply localized in the frequency domain and improve the denoising performance [5], downsamplers and upsamplers presented in the directional filter banks of SFLCT makes it lack shift-invariance, which could easily produce artifacts around the singularities, e.g. edges. Thus, Cycle Spinning is employed in this paper to compensate for the lack of translation invariance. It is a simple way yet efficient method to improve the denoising performance for a shift variant transform.

Suppose f and $\hat{f}$ are noisy and de-noised images, C and C_{-1} are the SFLCT forward and inverse transform, $S_{x,y}$ is the cycle spinning method and x, y are the shift arrange in horizontal and vertical directions, h is the denoising operation in the SFLCT domain, the denoising method by using Cycle Spinning-based Sharp Frequency Localized Contourlet Transform could be described as

$$\hat{f} = C_{-1}\left\{S_{-x,-y}\left\{h\left[C\left(S_{x,y}\left(f\right)\right)\right]\right\}\right\} \qquad (1)$$

Usually, $x \in X$ and $y \in Y$ which indicate a series of shift arranges $X = \{x_1, x_2, \cdots, x_m\}$ and $Y = \{y_1, y_2, \cdots, y_n\}$. If the size of noisy image is $M \times N$, the maximum shift $x_{\max} = \max(X)$ in horizontal direction must satisfy $x_{\max} \le M$ and the maximum shift $y_{\max} = \max(Y)$ in horizontal direction must satisfy $x_{\max} \le N$. Therefore, Cycle Spinning is to average out the translation dependence of subsampled directional filter banks as

$$\hat{f} = Ave_{x\in X, y\in Y}\left\{C_{-1}\left\{S_{-x,-y}\left\{h\left[C\left(S_{x\in X, y\in Y}\left(f\right)\right)\right]\right\}\right\}\right\} \qquad (2)$$

4. Numerical Experiments

In order to show the denoising performance of the proposed Cycle Spinning-based SFLCT (CS-SFLCT), it is compared with the original SFLCT [5] and contourlet (CT) [2] as well as the Cycle Spinning-based contourlet (CS-CT) [7], by using the standard hard thresholding denoising method. In the experiments, '9-7' and 'pkva' filters are used in pyramidal and directional decomposition, respectively.

In the first experiments, the image peppers added zero-mean Gaussian noise with different noise standard deviation σ and the series of shift arranges are set as $X = \{4, 16, 64\}$ and $Y = \{4, 16, 64\}$.

Fig.4 shows the PSNR of denoised image versus the standard deviation of noise using CT, CS-CT, SFLCT and CS-SFLCT, respectively. It shows that SFLCT outperforms CT more than 2 dB which is consistent with the results in [5]. Furthermore, the proposed CS-SFLCT yields 0.5 dB over SFLCT and obtains better visual effect, as shown in Fig.5, than SFLCT by averaging out the pseudo-Gibbs phenomena produced by the translation dependence.

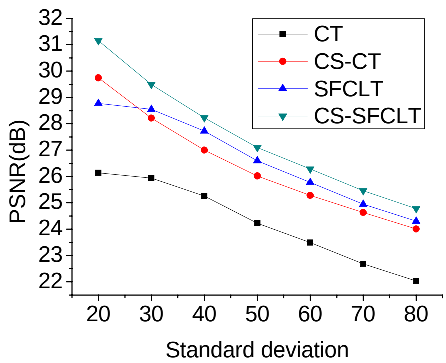


Fig.4 The PNSR values of denoised images versus the standard deviation of noise using four forms of contourlet.

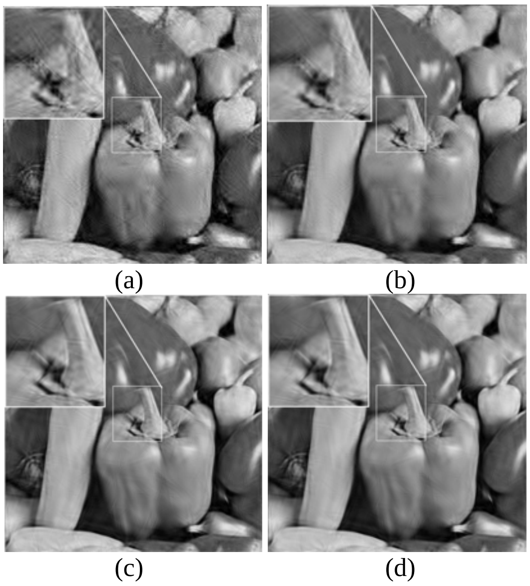


Fig.5 Denoised images when standard deviation of noise is 40. (a)-(d) are the denoised images using CT,CS-CT, SFLCT and CS-SFLCT.

Fig.6 shows the PSNR of denoised image versus different maximum shift arranges when standard deviation of noise is 40. In the experiments, $X = Y = \{4, 8, 12, \cdots, x_{\max}\}$ and the maximum shift arranges is changed from 4-pixels to 512-pixels distance which means $x_{\max} = 4i,\ i = 1, 2, 3, \cdots, 128$. The results shown in Fig.6 indicates that the PSNR increases quickly when maximum shift arrange $x_{\max}$ is small and almost does not increase when $x_{\max}$ reaches a certain constant, for example $x_{\max} = 52$ in this experiments for image *peppers* with 512×512 size. So, no matter for the SFLCT or CT, Cycle Spinning is an efficient and simple way to suppress the pseudo-Gibbs phenomena.

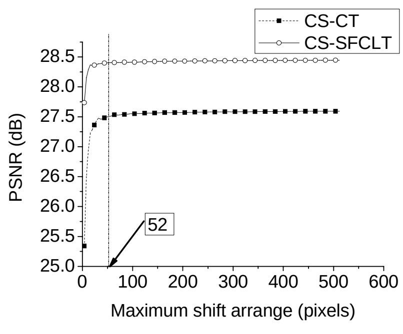


Fig.6 The PNSR values of denoised images versus different maximum shift arranges.

5. Conclusion and Discussion

In this paper, Cycle Spinning is employed to compensate for the lack of translation invariance property of Sharp Frequency Localized Contourlet. Experimental results demonstrate that Cycle Spinning is a simple and efficient way to average out the pseudo-Gibbs phenomena, which are around singularities and produced by the downsampling and upsampling of directional filter banks, and improve the denoising performance on visual effects and PSNR values, around singularities produced by the downsampling of directional filter banks. Furthermore, the original form and Cycle Spinning-based form of Sharp Frequency Localized Contourlet could be utilized in image fusion where nonsubsampled contourlet with great complexity to reduce the consuming time of fusion process [4] [8].

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References

[1] Pennec E, Mallat S, "Sparse geometric image representation with bandelets", *IEEE Transaction on Image Processing*, 2005, 14(4): 423-438.

[2] MN Do, M Vetterli, "The contourlet transform: an efficient directional multiresolution image representation", *IEEE Transaction on Image Processing*, 2005, 14(12): 2091-2106.

[3] Xiaobo Qu, Jingwen Yan, Guofu Xie, Ziqian Zhu, Bengang Chen, "A novel image fusion algorithm based on bandelet transform", *Chinese Optics Letters*, 2007, 5(10): 569-572.

[4] Xiao-Bo Qu, Guo-Fu Xie, Jing-Wen Yan, et al, "Image Fusion Algorithm Based on Neighbors and cousins information in Nonsubsampled Contourlet Transform Domain", *Proceedings of International Conference on Wavelet Analysis and Pattern Recognition*, IEEE ,Beijing China, 2007, 1797-1802.

[5] Yue Lu, MN Do, "A New Contourlet Transform with Sharp Frequency Localization", *Proceedings of 2006 IEEE International Conference on Image Processing*, IEEE, Atlanta, USA,2006, 1629-1632.

[6] R. R. Coifman ,D. L. Donoho, "Translation invariant de-noising," *Wavelets and Statistics*, A. Antoniadis and G. Oppenheim, Eds. New York: Springer-Verlag, 1995, 125–150.

[7] Eslami R , Radha H, "The contourlet transform for image denoising using cycle spinning", Proceedings of

Asilomar Conference on Signals ,Systems, and Computers, 2003,1982-1986.

[8] Qu Xiao-Bo, YAN Jing-Wen, XIAO Hong-Zhi, ZHU Zi-Qian. “Image Fusion Algorithm Based on Spatial Frequency-Motivated Pulse Coupled Neural Networks in Nonsubsampled Contourlet Transform Domain”. *Acta Automatica Sinica*, 2008, in press.