Contourlet Based Image Denoising Method Combined Recursive Cycle-Spinning Algorithm

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Abstract. Contourlet transform lacks shift invariance, and threshold processing on the coefficients may produce pseudo Gibbs phenomena. For recursive cycle spinning algorithm can reduce the pseudo Gibbs phenomena. This paper studies the image denoising method combined with Contourlet transform and recursive cycles pinning algorithm, The analysis show that the factor need to be adjusted. When the adjustment factor takes best value, the corresponding image objective index PSNR (Peak Signal to Noise Ratio) is the largest, and images visual effects are optimal. The experimental results show that: compared with original algorithm, changing adjustment factor, the PSNR of denoised image can be improved 0.6–1.2.

Keywords: Contourlet transform · Recursive cycle-spinning · Image denoising

1 Introduction

Image acquisition, transmission and storage process is limited by environmental conditions and physical limitations of imaging equipment. Different levels blur and noise will happened in those images, quality. i.e. images degradation. Image restoration technology obtained clear and high quality images from degraded images; it has been widely used in satellite image, industry and medical image processing.

Recent years, wavelet transform performs very well on image processing. However, a separable two-dimensional orthogonal wavelet transform has limited directionality and cannot effectively represent the direction information in image. Therefore it cannot effectively capture the contour and texture information. Wavelet transform can optimally represent piecewise smooth signals in one dimension, and capture point singularity of 1-D signal. Two-dimensional separable wavelet composed by tensor product can effectively capture single edge points in 2-D images. It is cannot optimally represent line singularities in 2-D images, such as the outline of object or a certain direction in image.

In 2002, Do and Vetterli proposed a two-dimensional representation of images [1]. Contourlet transform is a two-dimensional image sparse representation. It is more effectively capture high dimensional singularity. Compared with wavelet transform, the contourlet transform can expression small directional contours and line segments with

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fewer coefficients. Contourlet transform not only inherits the multi-resolution, localization and strict sampling characteristics of wavelet, but also has the characteristics of directionality and anisotropy. The contourlet transform can capture the edge details of images from different scales, different directions, and different frequencies. In image compression, denoising, feature extraction etc., can provide superior information. It has been widely used in image denoising, image fusion, digital watermarking etc., However, like wavelet transform, lacks translational invariance, the coefficients threshold processing in Contourlet transform also produce pseudo Gibbs phenomena. This phenomenon results in image distortion, and affects image visual effect. In 1995, the Cycle Spinning algorithms proposed by Coifman and Donoho [2], and the recursive cycle spinning proposed by Fletcher et al. [3, 4]. This algorithm can suppress pseudo Gibbs phenomenon and made threshold denoising more effectively. [5–7] have carried on correlation research.

This paper studied a Contourlet-Recursive cycle Spinning denoise method. It can obtained better visual image and higher PSNR by changing the adjusting factor.

2 Contourlet Transform

The base support interval of contourlet transform is 'Rectangle' structure. This rectangle is directional and anisotropic, and vary with aspect ratio.

The contourlet transform utilizes Laplace pyramid (LP) and directional filter bank (DFB) achieve multi-resolution, localization, multi direction decomposition.

Laplace pyramid (LP) decomposition was used to complete multi-scale decomposition. The LP decomposition at each level generates a down sampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image. Figure 1 depicts this decomposition process, where H and G are called (lowpass) analysis and synthesis filters. The outputs are a coarse approximation a and a difference b between the original signal and the prediction.

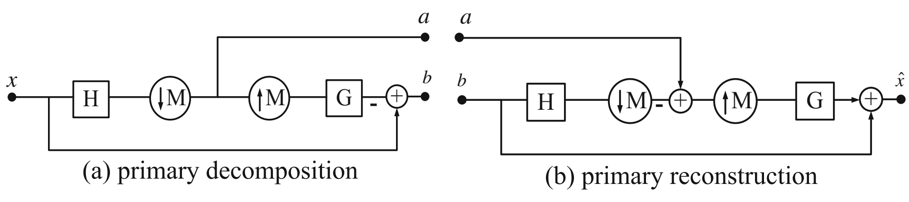

Fig. 1. Laplace pyramid decomposition and reconstruction

The wedge-shaped division of the directional filter banks is achieved by the directional frequency decomposition and resampling of the quincunx filter banks. The quincunx fan filter bank QFB is shown in Fig. 2. The signal is decomposed into basic vertical and basic horizontal subbands using H_0, H_1, G_0, G_1 quincunx filter banks. When they satisfy orthogonal or biorthogonal, complete reconstruction can be achieved.

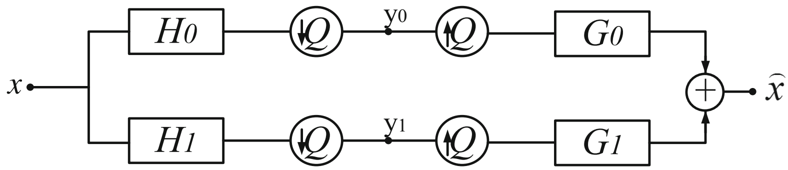

Fig. 2. Quincunx filter banks

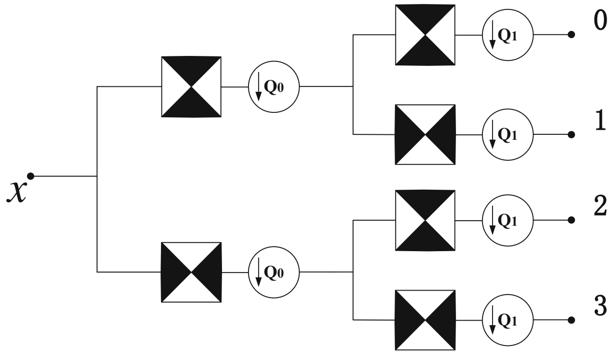

Fig. 3. The two layers of the DFB decomposition structure

The DFB is efficiently implemented via an l-level binary tree decomposition that leads to 2^L subbands with wedge-shaped frequency partitioning as shown in Fig. 3.

3 Recursive Cycle Spinning Algorithm

3.1 Recursive Cycle Spinning

The shift of the contourlet transform causes the pseudo Gibbs phenomenon in discontinuities signal, spurious Gibbs phenomenon means image distorted. To suppress the spurious Gibbs phenomenon in process of threshold denoising, inverse shift of denoised signal can make pseudo Gibbs phenomenon appear in different places, such as Eq. (1). Linear averaging of all the denoising results can inhibiting the pseudo Gibbs phenomenon, this is described as Eq. (2).

$$\hat{s}_{i,j} = C_{-i,-j}\left(F^{-1}\left(\theta\left(F\left(C_{i,j}(I(x,y))\right)\right)\right)\right) \tag{1}$$

$$\hat{s} = \frac{1}{N_1 N_2} \sum_{i=1,j=1}^{N_1 N_2} \hat{s}_{i,j} \tag{2}$$

Where, $I(x, y)$ is the gray value of noise image, N_1, N_2 is the maximum translation in row and column direction, C is the Cycle spinning operator, i, j is shift in row and column direction, F is a transform operator, F^{-1} is an inverse transformation operator, θ is threshold operator.

Usually, the average is not optimized, literature [3] proposes an recursive cycle spinning algorithm. The algorithm assumes that $\hat{s}_l$ represents an estimation sequence, the initial value is original noise signal, $\hat{s}_0[n] = I[n]$, iterate through Eq. (3).

$$\widehat{s}_{l+1} = D_i(\widehat{s}_l),\ i = l \bmod N \tag{3}$$

Where, $D_i(\bullet)$ is denoising operator, N is max displacement. In this algorithm, the sequence is shifted, transformed, threshold processed, inverse transformed, and the output sequence as input of next iteration operation. For all i, the fixed point $\hat{s}_\infty$ satisfy $\hat{s}_\infty = D_i(\hat{s}_\infty)$.

3.2 Denoising Algorithm

For image, the high frequency information is concentrated on the edges, contours, and normals of certain textures, represents the details of image changes. Therefore, the detail coefficients in directional subbands described high frequency information at each layer decomposition.

Stochastic characteristics of noise, leading it often appeared in high frequency information, and they are described by some detail coefficients. Those coefficients are quite small in general. After decompose at an appropriate scale, signal and noise often can be separated effectively. Contourlet threshold denoising achieved denoise by modifying the detail component coefficients of different scales.

The general steps of contourlet threshold denoising are described below:

(1) Multi-scale contourlet decomposition of image;
(2) According to the different characteristics of image and noise in Contourlet domain, the detailed component coefficients of each dimension are modified by setting threshold.
(3) Reconstruction image with the modified coefficients;

The modification of the detail component coefficients is key steps in image denoising processing, and it is affecting the final quality.

The hard threshold denoising mathematical expressions, such as Eq. (4):

$$T_{hard} = \begin{cases} W, & |W| \geq T \\ 0, & |W| < T \end{cases} \tag{4}$$

Where, W is contourlet coefficients of noise image, T is threshold.

In contourlet transform threshold denoise processing, the coefficients φ_{ct} should be determined. It can be expressed as Eq. (5):

$$\varphi_{ct} = \frac{4}{3}\lambda\delta\sqrt{\varphi_{yt}} \quad (5)$$

Where, φ_{ct} is sub-band adjusted coefficient,and φ_{yt} is the noise image each sub-band coefficients, λ is regulatory factor.

By changing λ, the sub-band coefficients φ_{ct} can be adjusted. λ affects the final denoising quality. λ is set by experience, and average is 3.

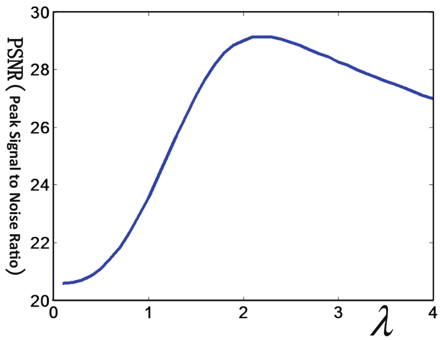

Fig. 4. The curves of PSNR

In this paper, the experimental results of Fig. 4 are obtained by adjusting the λ values. It can be seen that with the change of λ value, the PSNR value curve shows rise first and then decrease. When λ is 2.2, the maximum PSNR value is 29.2.

4 The Results of Simulation

In simulation experiment, when cycle times equal 10, the image distortion is well suppressed. This paper, the number of iterations is 10. The experimental image is 'lena.bmp (512 * 512)', The gaussian white noise $\sigma = 10$ are added to the standard image as noise image. The quality evaluation standard is PSNR. Contourlet transform choose '9–7' and 'pkva' filter.

The results are as follows:

Figure 5(c) is based on Contourlet transform denoising results, we can see that the denoised image has very serious pseudo Gibbs phenomena; Fig. 5(d), (e) and (f) are denoised image of this article algorithm, which pseudo Gibbs phenomena in those image has been reduced and the PSNR value of denoised image is improved. The values of λ in Fig. 5(d), (e), and (f) are 1.8, 2.2, 2.6, respectively. The PSNR of Fig. 5(e) is the largest, and it is visual effects are better. The larger λ value causes some blocky blur in recovery image, as shown in Fig. 5(f). It is concluded that the λ value should be set smaller. Otherwise, the denoised image may produce blocky blur, which is due to improper threshold selection. This affects the visual effect of denoised image. According to experimental results, it can be seen that the image denoising algorithm studied in this paper can improve the PSNR value, about 0.6–1.2.

(a) Lena raw image

(b) Noise image

(c) Lena recovery image，PSNR=28.0

(d) Lena recovery image, PSNR=28.6

(e) Lena recovery image, PSNR=29.2

(f) Lena recovery image, PSNR=28.8

Fig. 5. The results of simulation

5 Conclusion

In this paper we studied a image denoising method, which based on contourlet transform and recursive cycle spinning algorithm. Analyzed the influence of adjustment factor on denoising. From experimental results, when the adjustment factor equal 2.2, PSNR of denoised image is 29.2; the adjustment factor equal 1.8, PSNR is 28.6, and those images have better visual effects. Compared with the original algorithm, changing adjustment factor, the PSNR of denoised image can be improved 0.6–1.2.

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