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Research on wavelet-based contourlet transform algorithm for adaptive optics image denoising

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ABSTRACT

In this paper, we present a wavelet-based contourlet transform (WBCT) method to adaptive optics (AO) image denoising. This method is implemented through combining with BayesShrink theory to estimate the threshold and then improving the adaptive method of selecting threshold, finally obtaining the optimal threshold. The WBCT transform coefficients of different decomposition scales and different direction to select the adaptive optimal threshold to achieve denoising. We evaluate our algorithm using the DWT-NABayesShrink algorithm, DTCWT-BayesShrink algorithm and CbATD algorithm as a benchmark. Using simulated and real observed AO images, we show that our approach with WBCT algorithm exhibits better performance both in peak signal-to-noise ratio (PSNR) and visual quality, which opens up many perspectives for AO image denoising in the astronautics field.

1. Introduction

Because of the target background and the system's own factors, adaptive optics (AO) images contain a large amount of noise, which comes from the internal noise of sensor element, the quantization noise and transmission channel interference and so on. The noise will cause the target image is distorted seriously and impedes the target detection, tracking and positioning, so it is necessary to deal with the adaptive optics image denoising.

In recent years, many domestic and foreign scholars have proposed a number of denoising algorithms based on wavelet threshold. A universal threshold shrinkage method (VisuShrink) is proposed by Donoho and Johnstone [1], but with this algorithm the denoising image will appear ringing, too smooth, edge blur and the phenomena of lack of detail preservation. Kaur et al. [2] proposed a sub-band adaptive denoising method (NormalShrink). The method has the advantage of adaptive, according to different sub-bands of wavelet coefficients, it is possible to estimate the different threshold, however, the reservation of the details of the image still can not up to the requirements of denoising. Chang et al. [3] proposed adaptive wavelet threshold image denoising algorithm based on the principle of Bayesian (BayesShrink method). Contourlet transform proposed by Do and Vetterli [4] is a kind of multi-scale and multi-direction geometric transformation method, it inherits the multi-resolution of wavelet transform, and overcomes the problem of the nonlinear approximation of Ridge wave k error decay order and the redundancy of the Curvelet transform. This paper combines with the BayesShrink theory, improves threshold adaptive selection method, uses the wavelet-based contourlet transform (WBCT), so an adaptive optical image denoising algorithm based on WBCT is proposed.

2. Contourlet transform model based on wavelet domain

Discrete Contourlet transform is composed of Laplacian Pyramid (LP) and Directional filter banks (DFB) to form a double layer filter bank structure, also known as the tower direction filter group [5]. The specific process of the transformation: first of all, image is multi-scale decomposed by LP transform, and the singular points are obtained. Then the singular points at the same direction are decomposed by the DFB to synthesize a coefficient. Finally, the final result is similar to the base structure of the contour segment to approximate the original image. The process is shown in Fig. 1.

In this paper, we propose a Contourlet transform based on wavelet technique. Specific process is to first generate four directional sub bands LL, HL, LH and HH by using two-dimensional discrete wavelet transform, and use the 12 directions by 1–12 mark, WBCT has strict sampling data and contains the same size, which is in favor of image processing.

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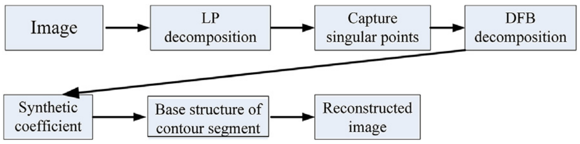

Fig. 1. Contourlet transform process.

2.1. The threshold calculation

The additive noise model of AO image can be defined as follows:

$$g(x, y) = f(x, y) + n(x, y) \tag{1}$$

where $f(x,y)$ is the noise free signal, $g(x,y)$ is observation to the original signal, $n(x,y)$ is Gaussian white noise, whose mean is 0 and variance is σ^2. The aim of denoising is to restore the original image from the noisy image g to maintain the image of f, and optimize the average variance.

In WBCT algorithm, select the threshold function and threshold are crucial. Threshold processing functions are commonly used in hard threshold and soft threshold function, and the soft threshold function is chosen in this paper. The soft threshold function is

$$\delta_s(x) = \begin{cases} x - T, & x > T \\ x + T, & x < -T \\ 0, & -T \le x \le T \end{cases} \tag{2}$$

In the formula, T is the threshold. In this paper, we use the Bayesian estimation criterion of literature [4] to estimate the threshold, the expression is

$$T_{i,j} = \frac{\hat{\sigma}_V^2}{\hat{\sigma}_x} \tag{3}$$

where $\hat{\sigma}_V^2$ is variance estimation of noise signal, $\hat{\sigma}_x$ is variance estimation of noise free signal.

The WBCT transform to formula (1):

$$C_{i,j} = X_{i,j} + V_{i,j} \tag{4}$$

where $C_{i,j}$ represent sub-band coefficients of the input image $g(x,y)$ of Contourlet transform decomposed. $X_{i,j}$ represents sub-band coefficients of the real image $f(x,y)$of the sub-band coefficients after wavelet decomposition, $V_{i,j}$ represent sub-band coefficients of the noise $n(x,y)$ of Contourlet transform decomposed.

Because $f(x,y)$ and $n(x,y)$ are independent of each other, according to formula (4):

$$\sigma_C^2 = \sigma_X^2 + \sigma_V^2 \tag{5}$$

The noise variance σ_V^2 is estimated by the coefficient of the first sub-band HH1, the expression is

$$\hat{\sigma}_V^2 = \frac{\text{Median}\left(\left|C_{i,j}\right|\right)}{0.6745}, \quad C_{i,j} \in \text{HH1} \tag{6}$$

The experiment shows that the effect of BayesShrink denoising is improved, but assuming that the wavelet coefficients are independent, it has not considered the correlation between the coefficients. So we need to further improve this method.

2.2. Adaptive threshold selection

According to the central limit theorem, the coefficients $C_{i,j}$ of the sub bands in the Contourlet decomposition are subordinate to the generalized Gauss distribution, the estimated formula for the variance σ_C^2 of sub band noise image in BayesShrink denoising is

$$\hat{\sigma}_C^2 = \frac{1}{m \times n}\sum_{k=1}^{m}\sum_{l=1}^{n}\left(C_{i,j}(k,l)\right)^2 \tag{7}$$

where σ_C^2 indicates that the variance of the sub-band $C_{i,j}$, $\hat{\sigma}_C^2$ is its estimation.

σ_C^2 depends on all the coefficients of the sub bands, in order to take into account the coefficients of locality and domain correlation, according to the characteristics of image to adaptive denoising, so we use WBCT to decompose the image, as far as possible to retain the image edge, texture and other details.

In this paper, the wavelet coefficients are processed by the neighborhood window, which is to estimate the noisy image variance of the current coefficients by calculating the variance of the noisy image within the window. Neighborhood window is the length N of the square, the center is the current coefficient, per unit of N is an interval of adjacent wavelet coefficients on the vertical or horizontal direction, the value of N can be 3×3, 5×5, 7×7, 9×9 etc. [6]. Assuming that in the size of the $m \times n$ sub band, the set of wavelet coefficients is $\{w_{p,q}\}$, the neighborhood window size is $N \times N$, the center position of the wavelet coefficient is $w_{p,q}$, the variance $\hat{\sigma}_{C,p,q}^2$ of the noisy image within the window is estimated to be

$$\hat{\sigma}_{C,p,q}^2 = \frac{1}{N^2}\sum_{k,l=1}^{N}\left|C_{i,j}(k,l)\right|^2 \tag{8}$$

In the formula, $C_{i,j}(k, l)$ represents a collection of wavelet coefficients in the neighborhood window.

In the $m \times n$ sub bands, the neighborhood variance of noisy image estimation is defined as follows:

$$\hat{\sigma}_C^2(\text{LD}) = \frac{1}{m \times n}\sum_{p=1}^{m}\sum_{q=1}^{n}\hat{\sigma}_{C,p,q}^2 \tag{9}$$

According to formulas (8) and (9), the neighborhood variance of the AO image is not dependent on all coefficients within the sub bands, but based on the neighborhood coefficients, which satisfies the local characteristics of the neighborhood. Therefore, in this method, the neighborhood variance $\hat{\sigma}_C^2(\text{LD})$ of the free noisy image is calculated with the local correlation.

By formula (5), the neighborhood variance estimation $\hat{\sigma}_X^2(\text{LD})$ of the noise free image can be obtained:

$$\hat{\sigma}_X^2(\text{LD}) = \hat{\sigma}_C^2(\text{LD}) - \hat{\sigma}_V^2 = \frac{1}{m \times n}\sum_{p=1}^{m}\sum_{q=1}^{n}\hat{\sigma}_{C,p,q}^2 - \frac{\text{Median}\left(\left|C_{i,j}\right|\right)}{0.6745} \tag{10}$$

In order to prevent the occurrence of negative values of $\hat{\sigma}_X^2(\text{LD})$, formula (10) is further modified:

$$\hat{\sigma}_X^2(\text{LD}) = \max\left(\left(\hat{\sigma}_C^2(\text{LD}) - \hat{\sigma}_V^2\right), 0\right) \tag{11}$$

Modify formula (3), the optimal threshold estimation for WBCT is obtained:

$$T_{i,j}\left(\hat{\sigma}_X(\text{LD})\right) = \frac{\hat{\sigma}_V^2}{\hat{\sigma}_X(\text{LD})} = \frac{\hat{\sigma}_V^2}{\sqrt{\max\left((\hat{\sigma}_C^2(\text{LD}) - \hat{\sigma}_V^2), 0\right)}} \tag{12}$$

In this paper, the threshold of image denoising algorithm is based on the statistical analysis of the noisy image data, the WBCT transform coefficients of different decomposition scales i and different direction j to select the adaptive optimal threshold