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Intensity image denoising for laser active imaging system using nonsubsampled contourlet transform and SURE approach

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ABSTRACT

This paper presents an algorithm based on nonsubsampled contourlet transform (NSCT) and Stein's unbiased risk estimate with a linear expansion of thresholds (SURE-LET) approach for intensity image denoising. First, we analyzed the multiplicative noise model of intensity image and make the non-logarithmic transform on the noisy signal. Then, as a multiscale geometric representation tool with multi-directivity and shift-invariance, NSCT was performed to capture the geometric information of images. Finally, SURE-LET strategy was modified to minimize the estimation of the mean square error between the clean image and the denoised one in the NSCT domain. Experiments on real intensity images show that the algorithm has excellent denoising performance in terms of the peak signal-to-noise ratio (PSNR), the computation time and the visual quality.

1. Introduction

Laser active imaging is able to produce both intensity and range images. These two images provide the full 3-D information of the target. During acquisition and transmission, intensity images are strongly affected by multiplicative noise, referred to as speckle noise, which reduces the effectiveness of visual interpretation and information extraction tasks. The main aim of intensity image denoising algorithm is then to reduce the noise level while preserving the image features. To develop effective noise-removing approaches, various filtering techniques have been proposed. Normally, they assume that statistical characteristics of the noise are available. Many researchers have also proposed wavelet-based approaches for this filtering problem. Among them, Luisier [1] developed the original Stein's unbiased risk estimate (SURE) [2] theory and proposed a general methodology for fast and efficient multidimensional image denoising, which is called the Stein's unbiased risk estimate with a linear expansion of thresholds (SURE-LET) [1,3–5].

Contrary to most existing denoising algorithms, SURE-LET does not require the explicit prior statistical modeling of the wavelet coefficients, it directly parameterize the denoising process as a sum of elementary nonlinear processes with unknown weights. The driving principle of SURE-LET is to minimize the estimation of the mean square error (MSE) between the clean image and the denoised one. Like the MSE, this estimation is quadratic in the unknown weights, and its minimization amounts to solve a linear system of equations. The existence of the estimation makes it unnecessary to devise a specific statistical model for the wavelet coefficients. Its effectiveness has been verified by simulation experiments [3–5]. For applications where textures are especially important, it maybe more effective to resort to transformations that better preserve high frequency directional details. The major drawback for wavelets in two-dimensions is their limited ability in capturing directional information. To overcome this deficiency, an emerging two-dimensional transform for image processing – nonsubsampled contourlet transform (NSCT) [6], which is a shift-invariant version of the contourlet transform, has been adopted to replace the wavelet transform in SURE-LET, since image denoising for additive noise in the NSCT domain generated better results than in the wavelet domain [7–9]. This modified denoising algorithm is denoted as NSCT based SURE-LET (NSCT SURE-LET).

This paper is organized as follows: In Section 2, we provide some background on the NSCT and SURE-LET. In Section 3, we extend the SURE-LET approach to the case of the NSCT, analyze the multiplicative noise model of the intensity image and show how to use the NSCT SURE-LET for intensity image denoising. In Section 4, we compare the performance of our proposed algorithm with the performance of current denoising methods applied to actual laser intensity images and quantify the achieved performance improvement. Finally, conclusions are drawn in Section 5.

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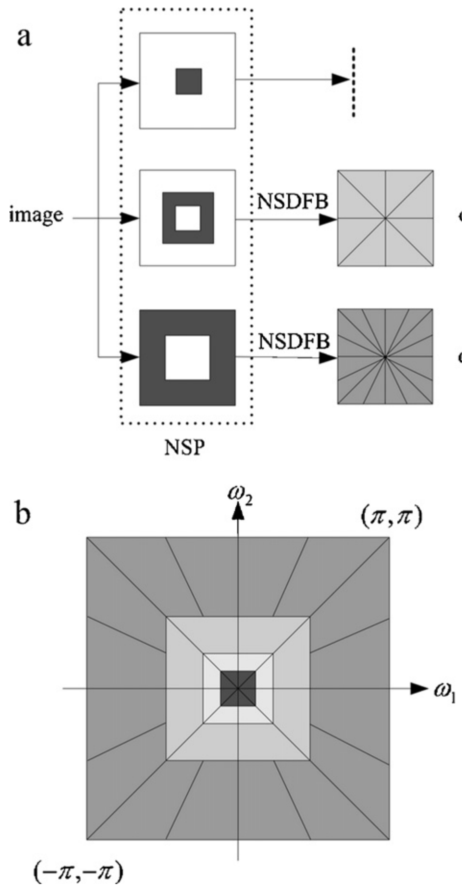

Fig. 1. The nonsubsampled contourlet transform. (a) Nonsubsampled filter bank structure that implements the NSCT. (b) The idealized frequency partitioning obtained with the proposed structure.

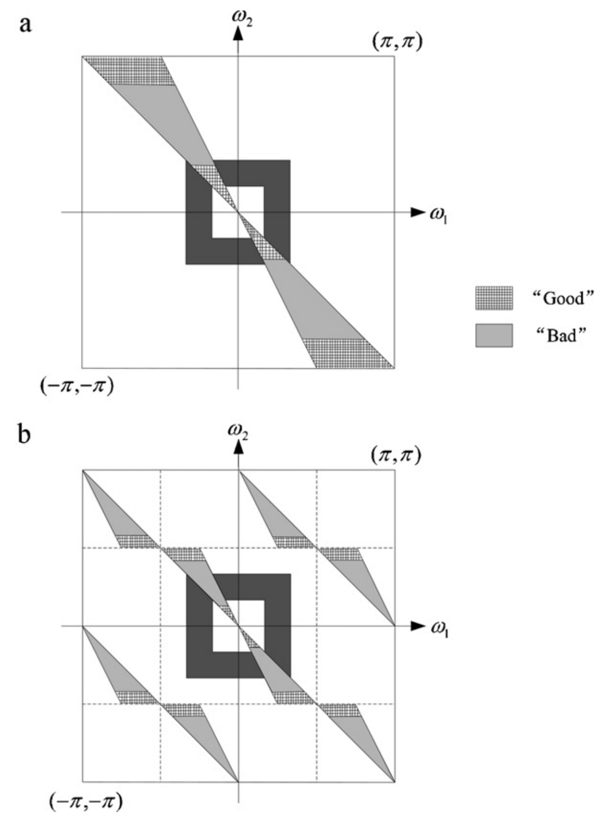

Fig. 2. The need for upsampling in the NSCT. (a) With no upsampling, the highpass at higher scales will be filtered by the portion of the directional filter that has "bad" response. (b) Upsampling ensures that filtering is done in the "good" region.

2. Theoretical background

2.1. The nonsubsampled contourlet transform (NSCT)

The NSCT has been proposed by Cunha and Do [6,7] in order to get rid of the frequency aliasing of contourlet and enhance its directional selectivity and shift-invariance. The NSCT provides a complete shift-invariant and multiscale representation, similar to the redundant wavelet transform, with a fast implementation. Here, we briefly introduce the construction of the NSCT. For the filter design, we refer readers to [6]. The contourlet transform employs Laplacian pyramids (LPs) [10,11], for multiscale decomposition, and directional filter banks (DFBs) for directional decomposition [12]. To achieve the shift-invariance, the NSCT is built upon nonsubsampled pyramids (NSPs) and nonsubsampled DFB (NSDFB) [6]. The NSCT is obtained via a two stage non shift-invariant process as depicted in Fig. 1. The first part achieves the multiscale property, via the NSP subband decomposition, while the second part provides directionality information using NSDFB. Both stages of the NSCT are constructed to be invertible in order to have an overall invertible system.

In constructing the NSCT, care must be taken when applying the directional filters to the coarser scales of the pyramid. Due to the tree-structure nature of the NSDFB, the directional response at the lower and upper frequencies suffers from aliasing which can be a problem in the upper stages of the pyramid. This is illustrated in Fig. 2(a), where the passband region of the directional filter is labeled as "Good" or "Bad". Thus, we see that for coarser scales, the highpass channel in effect is filtered with the bad portion of the directional filter passband. This results in severe aliasing and in some observed cases a considerable loss of directional resolution.

2.2. SURE-LET principle

We consider the standard denoising problem. Suppose the acquisition devices provide signals $y=[y_1, y_2, \ldots, y_N]$ that are corrupted with noise. Frequent modelization using an additive white Gaussian noise hypothesis

$$\underbrace{y}_{\text{“noisy” signal}} = \underbrace{x}_{\text{“original” signal}} + \underbrace{b}_{\text{“noise”}} \tag{1}$$

where $b=[b_1, b_2, \ldots b_N]$ is a white Gaussian noise of variance σ^2.

Our goal is to find a reasonably good estimate $\hat{\boldsymbol{x}} = \boldsymbol{F}(\boldsymbol{y}) = [f_1(y), f_2(y), \ldots f_N(y)]$ that minimizes the mean squared error (MSE) defined by

$$\text{MSE} = \frac{1}{N}\|\hat{x} - x\|^2 = \frac{1}{N}\sum_{n=1}^{N}(\hat{x}_n - x_n)^2 \tag{2}$$

2.2.1. Stein's unbiased MSE estimate (SURE)

Since we do not have access to the original signal $\boldsymbol{x}$, we cannot compute $\|\hat{x} - x\|^2/N$. However, without any assumptions on the noise-free data, we will see that it is possible to replace this quantity by an unbiased estimate which is a function of $\boldsymbol{y}$ only.

SURE is an unbiased statistical estimate of the mean squared error (MSE) between an original unknown signal and a processed version of its noisy observation. The following lemma (proved in [3]) which states a version of Stein's lemma [2], shows how it is possible to replace an expression that contains the unknown data