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Image denoising using multivariate model in shiftable complex directional pyramid domain and principal neighborhood dictionary in spatial domain

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ABSTRACT

The major challenge for image denoising is how to effectively remove the noise and preserve the detail information to get better visual quality and higher peak signal-to-noise ratio (PSNR). A new image denoising methods based on combination of multivariate shrinkage model in shiftable complex directional pyramid (PDTDFB) domain and principal neighborhood dictionary (PND) non-local means algorithm in spatial domain is proposed. In PDTDFB domain, the PDTDFB coefficients are modeled as multivariate non-Gaussian distribution taking into account the interscale and intrascale dependency correlation. Then a multivariate shrinkage function is derived by the maximum a posterior (MAP) estimator and the denoised coefficients are obtained. Although the PDTDFB-based algorithm achieves efficient denoising result, it is prone to producing salient artifacts which relate to the structure of the PDTDFB. Principal neighborhood dictionary (PND) is further employed to alleviate the artifacts with small computational load in spatial domain. Experimental results indicate that the proposed method is competitive with other excellent denoising methods in terms of PSNR value and visual quality.

1. Introduction

Images are inevitable to be corrupted by additive noise during acquisition or transmission. The noise usually can be modeled as Gaussian most of the time. Image denoising as a basis issue of image processing is always concerned by many researchers in recent decades. Plenty of denoising methods have been proposed, originating from various disciplines such as probability theory, statistics, partial differential equations, linear and nonlinear filtering, spectral and multiresolution analysis [1].

The wavelet transform used in image denoising as one of the most popular methods has received the some success due to its multiscale, multiresolution and sparse representation. Many wavelet-based shrinkage methods for image denoising have been developed, such as soft shrinkage [2], BayesShrink [3], BiShrink [4], SURE-based shrinkage [5]. However, wavelet transform only represents point-singularities efficiently. For line-singularities and curve-singularities that always exist in nature images, the wavelet transform cannot provide optimal sparse representation. In order to represent the high order singular feature better, some multiscale geometric analysis (MGA) tools have been put forward, such as ridgelet transform [6], curvelet transform [7], contourlet transform [8], shearlet transform [9] and shiftable complex directional pyramid (PDTDFB) decomposition [10]. The MGA tools provide much more directional selectivity than wavelets, and represent the contour and edge information of image much better. PDTDFB as a new MGA tool has good directional selectivity and optimal sparse representation with image edges. The denoising methods in transform domain are prone to produce salient artifacts such as low-frequency noise and edge ringing due to the structure of MGA tools. It is difficult to eliminate this phenomenon in transform domain.

In contrast, most algorithms based on the spatial domain can preserve the important image features and reduce low-frequency noise and edge ringing. Recently, the non-local means (NLM) algorithm that is introduced by Buades et al. [11] is an image denoising method in spatial domain which is based on the natural redundancy of information in images. This filter allows avoiding the well-known artifacts of the commonly used neighborhood filters [12]. In [11], comparing the NLM algorithm with some local smoothing filters, there are the non-presence of artifacts and the correct reconstruction of edges, texture and details. But the biggest

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drawback is the relatively high computational cost. Hereafter, plenty of improvements about NLM are put forward in order to achieve a higher accuracy and reduce the computational load [13–15]. In [15], an improved algorithm which is called principal neighborhood dictionary (PND) non-local means achieves a higher accuracy and smaller computational cost than the conventional NLM. PND uses principal component analysis (PCA) to project the image neighborhood vectors onto a lower-dimensional subspace for reducing the computational cost. Experiments demonstrate that PND is superior to the conventional NLM.

To obtain the good denoising performance while overcoming the problems of artifacts and the computational complexity, in this paper, we propose an image denoising method based on multivariate prior model by the maximum a posteriori (MAP) estimator in shiftable complex directional pyramid (PDTDFB) domain and PND in spatial domain. Firstly, noisy image is decomposed into different frequency sub-bands and orientation responses using PDTDFB. Secondly, based on the statistical dependencies among PDTDFB coefficients in interscale and intrascale, a multivariate non-Gaussian model is set up using the current coefficients, its neighborhood coefficients and its parent coefficients. Thirdly, the denoised PDTDFB coefficients are estimated by maximum a posteriori theory and a preliminary denoised image is obtained. Finally, so as to eliminate the salient artifacts of the preliminary denoised image, PND is used to enhance the denoising results. Experiments show that the proposed method could suppress the noise while preserving image details with admissible computational cost.

2. The shiftable complex directional pyramid (PDTDFB)

The shiftable complex directional pyramid is a novel image decomposition transform which is recently proposed in [10]. The image decomposition implemented by the PDTDFB transform is composed of a Laplacian pyramid and a pair of directional filter banks (DFBs) that is primal DFB and dual DFB. These two DFBs are constructed by using a binary tree of two-channel fan filter banks (FBs). The filters of FBs are implemented by phase compensation so that each pair of directional filters in the primal and dual DFBs form a Hilbert transform pair. In this way, a complex directional band pass sub-band is combined by the primal and dual DFBs which are corresponding to the real and imaginary parts of complex sub-band images. The input first image passes through an undecimated two-channel FB which satisfy the perfect reconstruction (PR) condition.

$$\left|R_0(\omega)\right|^2+\left|L_0(\omega)\right|^2=1 \tag{1}$$

The filter $L_0(z)$ is a wide-band low-pass filter while $R_0(z)$ is a high-pass filter complementing $L_0(z)$. After undecimated FB, the frequency components at $\omega_i=\pm\pi$ ($i=1, 2$) are removed so that the corresponding complex directional filters of the PDTDFB can be shiftable. At each scale, the PDTDFB consists of multiple levels of block P (and Q for the synthesis side) [10]. This block is composed of the filter $R_1(z)$, the filter $L_1(z)$ and a dual-tree DFB. The low-frequency component is fed into the second level decomposition, after being filtered by the low-pass filter $L_1(z)$ and decimated by $D=2I$. In order to create a PR FB, the filters in two blocks P and Q are designed to satisfy the unit transfer and zero aliasing condition.

$$\left|R_1(\omega)\right|^2+\frac{1}{4}\left|L_1(\omega)\right|^2=1 \tag{2}$$

Overall, the main design of the PDTDFB contains two parts: the design of two-channel FBs and the design of the fan FBs of the DFBs. The two two-channel FBs are used to create multiresolution decomposition. The first is the undecimated two-channel FB with two filters $R_0(z)$ and $L_0(z)$, the other is the multirate FB with two filters $R_1(z)$ and $L_1(z)$. For the DFBs, the fan FB of the second level of the binary-tree of the dual DFB is concerned which satisfies the phase constraints in [10].

The PDTDFB transform has the advantages as follow: multiscale and multidirectional transform, efficient implementation, high angular resolution, low redundant ratio, shiftable sub-bands, and provide local phase information. The PDTDFB transform has all the properties of contourlet transform and superior to contourlet transform in some respects. The PDTDFB decomposition is flexible and prefect reconstruction. Due to its many nice properties, the PDTDFB is suitable for applying in image processing.

3. Proposed image denoising method

3.1. Multivariate statistical model in PDTDFB domain

In this paper, the model of degraded image which is corrupted by white Gaussian noise follows as: $g(x,y)=f(x,y)+n(x,y)$, where $f(x,y)$, $g(x,y)$ and $n(x,y)$ respectively denote the clean image, the observed noisy image and the white Gaussian noise with zero mean. This model after linear transform to PFTDFB domain can be represented as:

$$y=c+\eta \tag{3}$$

where y, c and η are the noisy PDTDFB coefficients, the original PDTDFB coefficients and the noise coefficients. Many researches have revealed the strong dependencies of traditional wavelet coefficients in interscale and intrascale. And the PDTDFB coefficients have similar distribution characteristics with wavelet coefficients. In order to better capture the dependencies of PDTDFB coefficients, we propose a non-Gaussian density function to model the correlations among a current coefficient, its neighborhood coefficients and its parent coefficients. Then the multivariate MAP estimator is derived based on the framework of Bayesian theory. c_o, c_p and c_n are set to the clean PDTDFB coefficients, and c_p is the parent of c_o, c_n ($n=1,2,\ldots,k$) is the neighborhood of c_o. y_o, y_p and y_n ($n=1,2,\ldots,k$) are the corresponding noisy PDTDFB coefficients while η_o, η_p and η_n ($n=1,2,\ldots,k$) are zero mean white Gaussian noise coefficients. Then the model can be written as:

$$\begin{cases} y_o=c_o+\eta_o \\ y_p=c_p+\eta_p \\ y_n=c_n+\eta_n \end{cases}$$

The consequence is:

$$y=c+\eta$$

where $y=(y_o, y_p, y_1, y_2, \ldots, y_k)$, $c=(c_o, c_p, c_1, c_2, \ldots, c_k)$, $\eta=(\eta_o, \eta_p, \eta_1, \eta_2, \ldots, \eta_k)$.

The conventional MAP estimator for c is to maximize $p_{c|y}(c\,|y)$ can be expressed by

$$\hat{c}=\arg\max_c p_{c|y}(c\,|y)=\arg\max_c[\log(p_\eta(y-c))+\log(p_c(c))] \tag{4}$$

In the estimation process, the probability density functions of the noise coefficients and the noise-free coefficients should be given. Generally, the noise is assumed as i.i.d. zero mean Gaussian noise with variance σ_η^2. The probability density function is:

$$p_\eta(\eta)=\frac{1}{(2\pi\sigma_\eta^2)^{(k+2)/2}}\cdot\exp\left(-\frac{\eta_o^2+\eta_p^2+\eta_1^2+\eta_2^2+\cdots+\eta_k^2}{2\sigma_\eta^2}\right) \tag{5}$$

For a nature image, the experience histogram is usually employed to describe the approximate density function. Experiments reveal that the distribution of PDTDFB coefficients is same to the conventional wavelet coefficients which have the “heavy tail” characteristic that can be described by the prior