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Structure-adaptive Image Denoising with 3D Collaborative Filtering

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Abstract. As the state-of-art denoising method, BM3D is capable of achieving good denoising performance by exploiting both the non-local characteristics and sparsity prior knowledge of images. Nevertheless, experimental results show that the dissimilarity measurement defined in BM3D sometimes results in grouping patches with distinct structure. To improve the denoising effect furthermore, we propose a structure-adaptive image denoising method with 3D collaborative filtering by optimizing the block matching procedure, in which different types of patches are grouped in different ways. Considering the spatial similarity in smooth region, for smooth patches, we modify the original dissimilarity measurement by taking spatial distance into account. Moreover, inspired by the impact of noise on patches' variance, for non-smooth patches, we present the grouping approach based on dual thresholding, in which variance similarity is introduced to help group patches with similar structures. Several numerical experiments demonstrate that the proposed approach achieve better results in PSNR and visual effect than original BM3D.

Keywords: block matching, spatial similarity, variance, structure-adaptive

1 Introduction

Image denoising problem has drawn considerable research attention in past decades. It aims at separating the true signal from random noise. All the existing approaches rely on some explicit or implicit assumptions or prior knowledge of the noise-free image. Traditional means, such as Gaussian spatial filtering, exploit spatial similarity to remove noise. The non-local mean (NLM) [1] denoising method is a typical up-to-date example of this type. It exploits the inter-patch correlations and adopts neighborhood filters to reduce the noise by averaging similar pixels. However, due to the averaging operation, NLM method may give rise to over-smooth visual effect. In the recent years, sparse representation based methods have proven to be more effective in denoising. They take full advantage of sparsity prior knowledge of image in transform domain to

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attenuate noise. A typical instance is Wavelet shrinkage approach, which performs thresholding operation on wavelet coefficients to yield approximate estimate of original true image. To achieve good sparsity for spatially localized details, a variety of multiresolution transforms or overcomplete representations have been developed in shrinkage denoising methods [2-4].

BM3D [5] integrates both sparse representation and non-local averaging operation, and is widely recognized as the state-of-art denoising technique. By grouping similar patches together to form 3D array, it can achieve an enhanced sparse representation in transform domain, which ensures its outstanding denoising performance.

2 Related work about BM3D

As its name implies, BM3D involves two critical procedures: block matching and 3D collaborative filtering. Block matching is applied to find patches similar to a given reference one, in which it is important to define or compute the distance or dissimilarity between patches properly. The original BM3D uses the 2-norm distance to measure the dissimilarity. In order to avoid sharp drop of the output-PSNR in heavy noise, BM3D introduces coarse prefiltering into the block-distance measurement in the first stage's grouping, which is accomplished by applying hard-thresholding operator on the coefficients of a normalized 2D linear transform. Experimental results show that prefiltering may bring visual blocking effect and result in the removal of the true image signal [6]. Omid [7] proposed the accordingly improvement on BM3D by removing prefiltering and adjusting the parameters adaptively according to the estimated noise level.

In two denoising stages, collaborative filtering is performed by hard thresholding and wiener filtering respectively. During collaborative filtering, inseparability between noise and true signal may occur when patches can not be sparsely represented in 3D transform domain. It happens inevitably that filtering operation may remove partial energy of image signal. Furthermore, the weighted averaging behavior in aggregation actually acts as a low-pass filter, which may blur edges. To mitigate this drawback, Chen [8] proposed a bounded BM3D scheme, in which image is partitioned into multiple regions and a partial block matching is conducted when the reference patch contains several segments separated by edge. In fact, it is hard to recognize the boundary of multiple regions in a heavily noisy image, and erroneous region partitioning will pose a negative effect in block matching.

In order to enhance the denoising effects, Dabov [9] proposes a shape-adaptive collaborative filtering method, in which the shape of neighborhood can be selected adaptively and Shape-Adaptive DCT takes the place of DCT to perform 2D transform. On the basis of [9], Dabov[10] also incorporates Principle Component Analysis (PCA) into BM3D and designs the improved BM3D method with shape-adaptive PCA. Both methods in [9][10] are invalid for a heavily noised image, because when the image is immerged in strong noise and it is tough to discern the shape of neighborhood.

In this paper, we propose an improved BM3D denoising method with structure-adaptive block matching measurement scheme. Inspired by the characteristics of the variance, we adopt dual thresholding scheme in block matching procedure by incorporating the variance into finding similar blocks. Additionally, considering the strong correlation in smooth region, we take spatial distance into account when computing the dissimilarity between two patches. Numerical experimental results illustrate that the proposed method could achieve better performance in image denoising.

3 Structure-adaptive BM3D denoising scheme (SA-BM3D)

In BM3D, grouping procedure begins with block matching to find similar fragments relative to the reference block. Only fragments whose distance with respect to the reference one is smaller than a fixed threshold are considered similar. Generally, it is effective to adopt the 2-norm distance to compute the dissimilarity. Nevertheless, experimental results show 2-norm measurement may result in erroneous grouping possibly even for clean images. To eliminate the erroneous grouping like this, some extra information about blocks' structure needs to be merged into dissimilarity measurement. Recall that variance is capable of measuring the complexity of image patches in texture or structure to some extent, and patches with similar structure may have similar variances. When patches are polluted with noise, the variance of them will increase inevitably. Smooth patches are more susceptible to noise than non-smooth ones. And the block matching procedure on smooth patches is prone to generate more 'pseudo-similar' patches.

In order to decrease the error probability in grouping, we put forward a structure-adaptive grouping approach. The basic idea is to select block matching scheme adaptively according to the structure type of the reference patch. In the smooth region of a given image, patches in the neighborhood are more likely to be correlative and become mutual similar ones. And the dissimilarity is computed by taking the local spatial distance between patches into account, and an additional scalar weight is introduced in the original 2-norm measurement, as shown in Eq.(1). For patches which contain complex texture details, variance is integrated into the original block matching procedure and dual thresholding operator is applied to select similar patches, as shown in Eq. (3). In other words, the patches are considered as similar ones only when dissimilarity in both pixel and variance do not exceed two predefined thresholds at the same time.

$$d^{p}(Z_{x_R}, Z_x) = w(Z_{x_R}, Z_x)\frac{\left\| Z_{x_R} - Z_x \right\|_2^2}{(N_1^{ht})^2} \tag{1}$$

$$w(Z_{x_R}, Z_x) = \frac{1}{1 + e^{(-\left\| x_R - x \right\|_2 / h)}} \tag{2}$$

$$G_{x_R}^{ht} = \{x \in X : d(Z_{x_R}, Z_x) \leq \tau_1^{ht} \,\&\&\, \mathrm{abs}(std(Z_{x_R}) - std(Z_x)) \leq \tau_2^{ht}\} \quad (3)$$

4 Simulation results

To validate the improvement of the proposed approach over original BM3D, we implement the corresponding simulation programs in matlabR2012a. The standard test images we select include Barbara, Lena, peppers, which show different features in texture structure. And the configuration of parameters adopted in our simulation refers to the normal profile in [5].Table 1 compares the PSNR (dB) performance of the proposed algorithm with BM3D in denoising images with noise level at σ =20, 30, 40, 50, 60 respectively. In Table 1, the column of 'scheme I' shows the PSNR results when Eq. (1) is adopted to group similar patches; The column of 'scheme II' displays the PSNR results when dual-thresholding in Eq. (3) is applied to all reference patches to select similar ones. The right-most column provides the denoising results when the grouping procedure uses the structure-adaptive block matching method proposed in section 3, which combines scheme I and scheme II. Obviously, compared with original BM3D, all three schemes identified with 'scheme I', 'scheme II' and 'combined' achieve better results in PSNR. Moreover, it can be clearly seen from Table I that scheme II outperforms scheme I in general cases while 'peppers' is an exception. When denoising 'peppers' image with noise level at $\sigma \geq 40$ scheme I gets better outcome than scheme II. The major reason for this exception is that in 'peppers', the smooth patches account for most part and consequently, the effect of denoising assisted by variance in heavy noise is weakened. Also we note that the joint scheme identified with 'combined' is inferior to scheme II when denoising the 'barbara' image, which may be caused by existence of lots of texture in the image.

Fig. 1 compares the visual effect of denoising images in the proposed method and original BM3D. From Fig. 1, we can see that the proposed method can retain more detail information and images in column (d) contains more clear texture than that of column (c).

5. Conclusions

In order to group as few pseudo-similar patches as possible, the structure-adaptive block matching algorithm is presented in this paper. For non-smooth patches, we propose an improvement on the original 2-norm distance measurement by incorporating the similarity in the variance between patches to find mutual similar ones. For smooth ones, based on the prior knowledge of correlation among patches in the same neighborhood, the 2-norm dissimilarity measurement is modified by adding an extra scalar weight, which depends on the spatial distance between the reference patch and the candidate. Simulation results demonstrate the proposed method outperforms the original BM3D in both PSNR and visual quality at the cost of extra computational overhead.

Table 1. PSNR(dB) COMPARISON BETWEEN our proposed method AND original BM3D

σ	image	BM3D	Scheme I	Scheme II	Combined
20	Lena	32.75	32.78	32.86	32.87
	Peppers	32.37	32.41	32.44	32.45
	Barbara	31.90	31.96	32.09	32.06
30	Lena	30.88	30.94	30.96	30.98
	Peppers	30.76	30.81	30.83	30.85
	Barbara	29.65	29.72	29.79	29.77
40	Lena	29.44	29.52	29.53	29.55
	Peppers	29.30	29.33	29.31	29.39
	Barbara	27.86	27.91	27.97	27.95
50	Lena	28.74	28.83	28.88	28.90
	Peppers	28.75	28.82	28.79	28.83
	Barbara	27.14	27.21	27.33	27.32
60	Lena	27.89	27.98	28.03	28.04
	Peppers	27.78	27.87	27.83	27.91
	Barbara	26.24	26.33	26.42	26.43

(a) clean image (b) noisy image(σ =40) (c) original BM3D (d) the proposed method

Fig. 1. comparison of visual denoising effect

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