International Journal of Scientific Research in Computer Science, Engineering and Information Technology
 | Volume 2 | Issue 3 | ISSN : 2456-3307

Two Phase Image Denoising By Principal Component Analysis and Local Pixel Grouping

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ABSTRACT

This paper presents an efficient image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG). For a better preservation of image local structures, a pixel and its nearest neighbors are modeled as a vector variable, whose training samples are selected from the local window by using block matching based LPG. Such an LPG procedure guarantees that only the sample blocks with similar contents are used in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise. The LPG-PCA denoising procedure is iterated one more time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms.

Keywords: Denoising, Principal Component Analysis, Edge Preservation

I. INTRODUCTION

Noise will be inevitably introduced in the image acquisition process and denoising is an essential step to improve the image quality. In the proposed LPG-PCA, we model a pixel and its nearest neighbors as a vector variable. The training samples of this variable are selected by grouping the pixels with similar local spatial structures to the underlying one in the local window. With such an LPG procedure, the local statistics of the variables can be accurately computed so that the image edge structures can be well preserved after shrinkage in the PCA domain for noise and the image edge structures can be well preserved after shrinkage in the PCA domain for noise removal.

II. LITERATURE REVIEW

As a primary low-level image processing procedure, noise removal has been extensively studied and many denoising schemes have been proposed, from the earlier smoothing filters and frequency domain denoising methods [14] to the lately developed wavelet [1], curvelet [5] and ridgelet [6] based methods, sparse representation [7] and K-SVD [8] methods, shape-adaptive transform [9], bilateral filtering [10], non-local mean based methods [11] and non-local collaborative filtering [12]. With the rapid development of modern digital imaging devices and their increasingly wide applications in our daily life, there are increasing requirements of new denoising algorithms for higher image quality.

Wavelet transform (WT) [13] has proved to be effective in noise removal [4]. It decomposes the input signal into multiple scales, which represent different time-frequency components of the original signal. At each scale, some operations, such as thresholding [2] and statistical modeling [3], can be per- formed to suppress noise. Denoising is accomplished by trans-forming back the processed wavelet coefficients into spatial domain. Late development of WT denoising includes ridgelet

III. PROBLEM DEFINITION

For natural images, however, there is a rich amount of different local structural patterns, which cannot be well represented by using only one fixed wavelet basis. Therefore, WT-based methods can introduce many visual artifacts in the denoising output. To overcome the problem of WT, in [21] Muresan and Parks proposed a spatially adaptive principal component analysis (PCA) based denoising scheme, which computes the locally fitted basis to transform the image. Elad and Aharon [13] proposed sparse redundant representation and K-SVD based denoising algorithm by training a highly over-complete dictionary. Foi et al. [15] applied a shape-adaptive discrete cosine transform (DCT) to the neighborhood, which can achieve very sparse representation of the image and hence lead to effective denoising. All these methods show better denoising performance than the conventional WT-based denoising algorithms.

IV. METHODOLOGY

As shown in Figure, the proposed LPG-PCA algorithm has two stages. The rest stage yields an initial estimation of the image by removing most of the noise and the second stage will further refine the output of the first stage. The two stages have the same procedures except for the parameter of noise level. Since the noise is significantly reduced in the first stage, the LPG accuracy will be much improved in the second stage so that the final denoising result is visually much better. Compared with WT that uses a fixed basis function to decompose the image, the proposed LPG-PCA method is a spatially adaptive image representation so that it can better characterize the image local structures. Compared with NLM and the BM3D methods, the proposed LPG-PCA method can use a relatively small local window to group the similar pixels for PCA training, yet it yields competitive results with state-of-the-art BM3D algorithm.

Input Image ➔ Adding Noise

Denoised image after the first stage of the proposed method ➔ Denoised image after the second stage of the proposed method

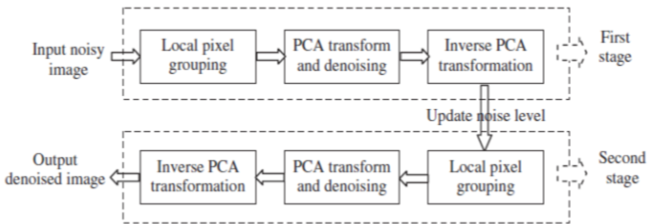
Figure 1: Flowchart of the proposed two-stage LPG-PCA denoising scheme

V. RESULTS AND DISCUSSION

We first verify the improvement of the noise removal in the second stage of the PLG-PCA method. Table 1 lists the PSNR and SSIM measures of the first stage and second stage denoising outputs on the test image set. We can see that the second stage can improve 0.1-1.5dB the PSNR values for different image sunder different noise level (s is from10to40). Although for some images the second stage will not improve much the PSNR measures, the SSIM measures, which can better reflect the image visual quality, can be much improved. For instance, for image Lena with noise level s=30, the SSIM measure is much increased from 0.7441 to 0.8066 after the second stage denoising, while the PSNR is increased by only 0.5dB.

Table 1

Methods	[10]	[8]	[14]	[20]	Proposed
L e n a					
s=10	33.1(0.9154)	33.2(0.9160)	33.5(0.9203)	33.9(0.9272)	33.7(0.9243)
s=20	29.2(0.8455)	29.4(0.8514)	29.7(0.8571)	30.2(0.8699)	29.7(0.8605)
s=30	27.2(0.7878)	27.5(0.7964)	27.8(0.8055)	28.3(0.8231)	27.6(0.8066)
s=40	25.7(0.7315)	26.0(0.7466)	26.2(0.7504)	27.3(0.7727)	26.0(0.7578)



VI. CONCLUSION

This paper proposed a spatially adaptive image denoising scheme by using principal component analysis (PCA). To preserve the local image structures when denoising, we modeled a pixel and its nearest neighbors as a vector variable, and the denoising of the pixel was converted into the estimation of the variable from its noisy observations. The PCA technique was used for such estimation and the PCA transformation matrix was adaptively trained from the local window of the image. However, in a local window there can have very different structures from the underlying one; therefore, a training sample selection procedure is necessary. The block matching based local pixel grouping (LPG) was used for such a purpose and it guarantees that only the similar sample blocks to the given one are used in the PCA transform matrix estimation. The PCA transformation coefficients were then shrunk to remove noise. The above LPG- PCA denoising procedure was iterated one more time to improve the denoising performance. Our experimental results demonstrated that LPG-PCA can effectively preserve the image fine structures while smoothing noise. It presents a competitive denoising solution compared with state-of-the-art denoising algorithms, such as BM3D.

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