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Image Denoising by using Local Pixel Grouping with PCA and SVD along with JBF and Median Filters

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ABSTRACT

This paper proposed a new technique for image denoising [1] [2] [8] [10] [14] using local pixel grouping, SVD and Joint Bilateral Filter. The paper also proposed use of LPGSVD with median filter. It is found that bilateral filter technique works well for Gaussian noise [22] whereas median filter when applied to the output of LPGSVD improves results for salt & pepper noise [22]. The results are compared using PSNR and SSIM [16] performance metrics.

General Terms

Image Processing, Image Restoration.

Keywords

Image Restoration, LPGPCA, LPGSVD, Joint Bilateral Filter, Median filter, Image denoising.

1. INTRODUCTION

Image Restoration [20] is the process of reconstruction of the original image from degraded image [20]. Many times, during the process of image formation itself image gets degraded, so it is hard to avoid it. If imaging conditions are not favorable for example moving vehicle, images of stars, planets, artificial satellites, etc where atmospheric turbulence affects quality of images, it is more challenging to restore the images. For an observed image y, the problem of image restoration (IR) can be generally formulated by

$$y=H * x + v \tag{1}$$

where H is a degradation matrix, x is the original image and v is the additive noise. Different IR problems can be specified by same equation by using different values of H, for example when H is an identity matrix it is called image denoising, when H is a blurring operator it is called image deblurring, when H is a composite operator of blurring and down-sampling [11] is called image super resolution [11].

Generally, image restoration approaches can be categorized as spatial domain, transform domain [3] [4], and dictionary learning based [7] [8] [10] [11] [12] [13] according to the image representation. Spatial domain methods include local and nonlocal filters [1] [2], which exploit the similarities between either pixels or patches in an image. Both transform domain and dictionary learning based methods [7] [8] [10] [11] [12] [13] consider transforming images into other domains, where similarities of transformed coefficients are measured. The difference between them is that transform domain approaches [5] [6] [9] usually represent images with fixed basis functions, but learning-based methods use sparse representations based on a redundant dictionary [7] [8] [10] [11] [12] [13]. Examples of dictionary learning based methods are K-SVD [7], KLLD [10], NCSR [11], etc.

Statistically, PCA [18] is a de-correlation technique and it is used mainly in pattern recognition and dimensionality reduction. If we transform the original dataset in PCA domain, and conserve only the most significant principal components, the noise and trivial information can be removed.

SVD [18] is also matrix decomposition technique. Using singular value decomposition, any real matrix P can be decomposed into a product of three matrices U, S and V as $P=USV^T$, where U and V are orthogonal matrices and S is diagonal matrix. If P is of size m x n then U is of size m x m orthonormal matrix and it’s columns are called as left singular vectors of P and V is of size n x n orthonormal matrix and it’s columns are called right singular vectors of P [18].

Some properties of SVD which are useful in image processing are:

- The singular values are unique for a given matrix [18].
- The rank of matrix A is equal to its nonzero singular values [18]. In many applications, the singular values of a matrix decrease quickly with increasing rank. Using this property we can reduce the noise or compress the matrix data by considering only some higher singular values or the lower ranks.
- The singular values of an image have very good stability i.e. when a small perturbation is added to an image; its singular values don’t change significantly [18].

SVD based technique based on aggregation is developed in [15].

The bilateral filter [19] is sort of nonlinear filter that calculates weighted average of pixels. The bilateral filter considers intensity variation to preserve edges. In bilateral filtering two pixels are close to each other if they occupy nearby spatial locations and also if they have some similarity in the photometric range.

This paper analyses the image denoising [1] [2] [8] [10] [14] techniques based on local pixel grouping and PCA, SVD decomposition and effects of filters along with them for example bilateral filter, median filter, etc. This paper discusses novel techniques using SVD and bilateral filter and SVD with median filter.

2. OVERVIEW OF LPGPCA AND JBF

In image denoising by using local pixel grouping using principal component analysis [14] and joint bilateral filter [17] the main steps are

1) Local Pixel Grouping [14]
2) PCA transform and denoising

3) Inverse PCA transform

4) Applying JBF on result of LPGPCA and original noisy image

LPG-PCA uses a moving window to calculate the local statistics, and then calculate local PCA transformation matrix. The algorithm has two stages, in the first stage it gives an initial estimation of the image by removing a large amount of the noise and the second stage will further refine the output of the first stage [14].

Steps involved in calculation of PCA are:

1) Subtraction of mean

2) Calculation of covariance matrix

3) Calculation of eigen vector and eigen values.

4) Multiply eigen vector and image

Noise is suppressed by using linear minimum mean square error estimation (LMMSE) technique [14]. Shrinkage coefficient is multiplied with covariance values and then mean values are added back to get denoised dataset.

In LPGPCA-JBF third stage is added, in which LPGPCA result is used as reference image for Joint Bilateral Filter (JBF) to preserve and enhance the edges effectively [17].

3. OVERVIEW OF LPGSVD

In the LPGSVD method [21] SVD decomposition is used for image denoising [1] [2] [8] [10] [14]. Procedure of The local pixel grouping and refinement in stage 2 is same as that of LPG_PCA.

3.1 Local Pixel Grouping

Since the observed image is noise corrupted, it is denoted as X_v=X+V. In order to remove the noise from X_v by using SVD, a training samples of size (L x L) is selected and in that a variable block of size (K x K) is chosen, (K<L). Total $(L\text{-}K+1)^2$ training samples are used. Out of these $(L\text{-}K+1)^2$ training samples, training samples that are similar to central K x K block are selected and grouped by subtracting all $(L\text{-}K+1)^2$ entries from K x K block elements and then results are compared with preset threshold. Accordingly some sample vectors are selected for further calculations.

3.2 SVD Based Algorithm

In the SVD based algorithm [21] steps involved are:

1) Subtraction of mean

2) Calculate SVD as A= U∑V, it is similar to calculate the eigen values and eigen vectors of AA^T (U) and A^TA (V), the singular values in **S** are square roots of eigenvalues from AA^T or A^TA [18].

3) Multiply singular values and image.

4) Using weight calculation reduces the noise in image.

3.3 Refinement in stage 2

The second stage has the same procedure like stage 1, except for the parameter of noise level. In this stage weight is calculated using difference between original noisy image and output of stage 1. Since the noise in the first stage is significantly reduced, the LPG accuracy will be much improved in the second stage so that the final denoising result is much better.

4. PROPOSED TECHNIQUES

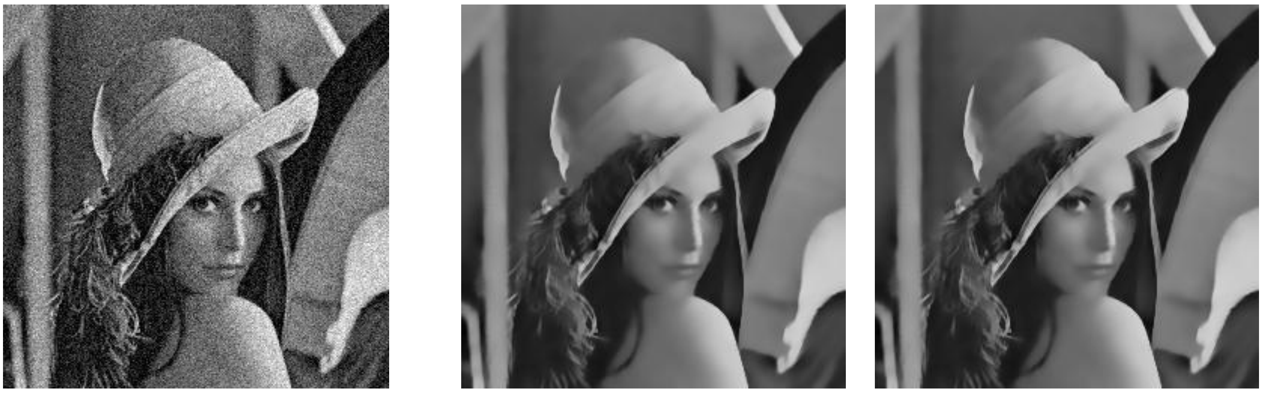
In this paper effects of different filters in combination with LPGPCA and LPGSVD are analyzed. Joint bilateral filter [19] is applied on the output of LPGSVD technique and compared with LPGPCA followed by bilateral filtering approach [17]. Bilateral filter [19] gives good results for Gaussian Noise [22] so these techniques are checked against it. Median filter [22] is applied as post processing on LPGSVD technique [21] and results are improved for salt & pepper noise [22].

5. RESULTS

The techniques LPG-PCA-JBF and LPG-SVD-JBF are applied on gray images and results are compared using PSNR and SSIM [16] objective criteria. Figure 1 and 2 shows the output images when these two techniques are applied on house and Lena images respectively. Table 1 compares the results for 3 gray images using PSNR and SSIM [16]. LPG-SVD followed by median filtering is applied on gray as well as color images. Figure 3 and 4 shows results for LPGSVD and LPGSVD +Median filter on house and Lena gray images respectively. Table 2 compares results for 3 gray images using PSNR and SSIM [16]. Figure 5 shows results for LPGSVD and LPGSVD +Median filter on parrot color image. Table 3 compares results for this color images using PSNR and SSIM [16]. It is found that bilateral filter technique works well for Gaussian noise [22] and median filter when applied to the output of LPGSVD improves results for salt & pepper noise [22] in terms of PSNR and SSIM [16].

Noisy Image LPGPCAJBF LPGSVDJBF

Figure1: Results of LPGPCAJBF and LPGSVDJBF on house image affected by Gaussian noise.

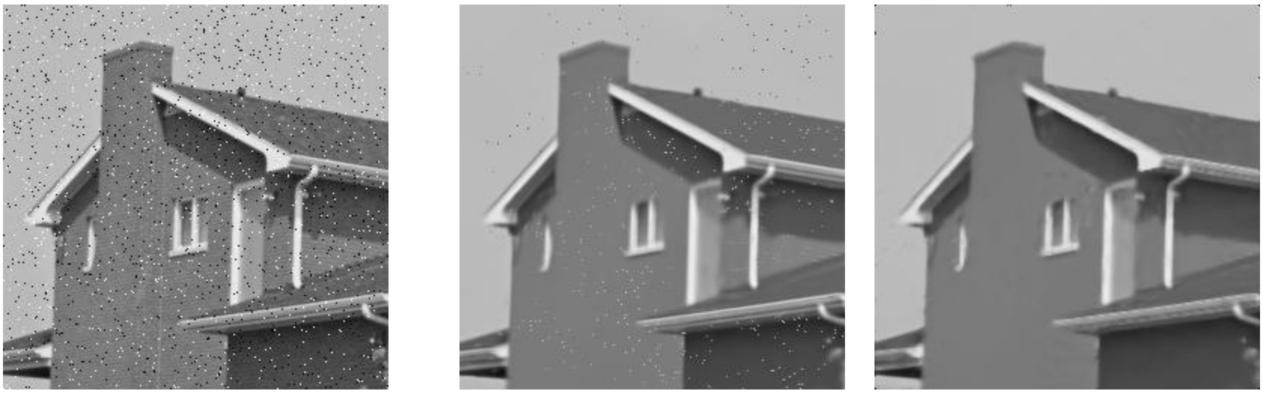


Noisy Image LPGPCAJBF LPGSVDJBF

Figure 2: Results of LPGPCAJBF and LPGSVDJBF on Lena image affected by Gaussian noise

Table 1: Comparison of Results of LPGPCAJBF and LPGSVDJBF on 3 gray images affected by Gaussian noise.

	PSNR		**SSIM**	
Images/Techniques	LPGPCAJBF	LPGSVDJBF	LPGPCAJBF	LPGSVDJBF
House	**31.3983**	**31.3983**	**0.8344**	**0.8344**
Lena	**28.6547**	**28.6547**	**0.8182**	**0.8182**
Monarch	**28.7509**	**28.7509**	**0.8804**	**0.8804**



Noisy Image LPGSVD LPGSVD+Median

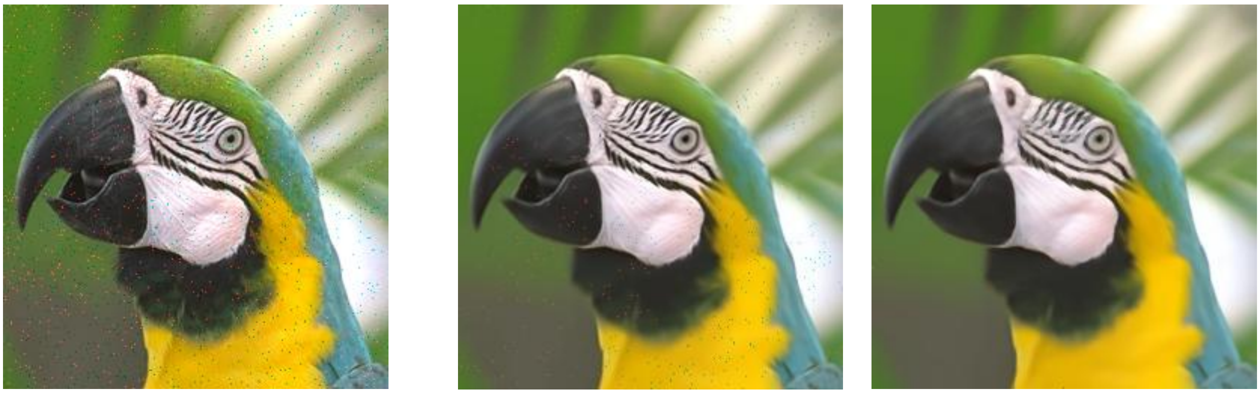
Figure 3: Results of LPGSVD and LPGSVD+Median filter on house image affected by Salt & pepper noise [22].

Noisy Image LPGSVD LPGSVD+Median

Figure 4: Results of LPGSVD and LPGSVD+Median filter on Lena image affected by Salt & pepper noise [22].

Table 2: Comparison of Results of LPGSVD and LPGSVD+Median filter on 3 gray images affected by Salt & pepper noise [22].

	PSNR		SSIM	
Images/Techniques	LPGSVD	LPGSVD+Median	LPGSVD	LPGSVD+Median
House	29.8963	**31.2342**	0.7829	**0.8425**
Lena	26.2075	**28.7877**	0.7717	**0.8422**
Monarch	27.0868	**28.5597**	0.8350	**0.9016**



Noisy Image LPGSVD LPGSVD+Median

Figure 5: Results of LPGSVD and LPGSVD+Median filter on parrot image affected by Salt & pepper noise [22].

Table 3: Comparison of Results of LPGSVD and LPGSVD+Median filter on parrot color images affected by Salt & pepper noise [22].

	PSNR		SSIM	
Images/Techniques	LPGSVD	LPGSVD+Median	LPGSVD	LPGSVD+Median
Parrot	30.2879	**30.9198**	0.8683	**0.8976**

6. CONCLUSION

This paper proposed a unique technique for image denoising, using local pixel grouping SVD and Joint Bilateral Filter. The paper also proposed use of LPGSVD with median filter. It is found that bilateral filter technique works well for Gaussian noise [22] whereas median filter when applied to the output of LPGSVD improves results for salt & pepper noise [22]. The results are compared using PSNR and SSIM [16] performance metrics with existing LPG-PCA-JBF technique and developed LPG-SVD technique. In future LPGPCA and LPGSVD both techniques can be extended using different kinds of filters such as bilateral filter, mean filter, min max filter, etc.

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