# Two-stage image denoising by Principal Component Analysis with Self Similarity pixel Strategy

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**Abstract:**
This paper presents an efficient image denoising scheme by using principal component analysis (PCA) with self similarity pixel strategy (SSS). 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 self similarity driven strategy. Such an SSS 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. i.e. Color information present in the raw image can be transported from pixels where it is known to pixels where it is different based on local similarities. The image data obtain from PCA denoising procedure is passed through the SSS-PCA denoising procedure to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. Proposed algorithm find out the missing color components in the mosaic images captured by the CFA and improve the visual quality of the resulting output.

***Keywords:***
*Demosaicking, Gradient, Mosaic Image, Local Similarities, Mosaic, CFA*

## 1. 1. INTRODUCTION

Noise will be inevitably introduced in the image acquisition process and denoising is an essential step to improve the image quality. 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 [25] to the lately developed wavelet [1–10], curvelet [11] and ridgelet [12] based methods, sparse representation [13.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.

Denoising is accomplished by transforming back the processed wavelet coefficients into spatial domain. To overcome the problem of WT, a spatially adaptive principal component analysis (PCA) based denoising scheme, which computes the locally fitted basis to transform the image. Later introduced methods show better denoising performance than the conventional WT-based denoising algorithms. Inspired by the success of combination of both poisson distributive noise detection and nearest neighborhood approach has provided good output for the raw images.

In this paper we present an efficient PCA-based denoising method with self similarity pixel strategy (SSS). PCA is a classical de-correlation technique in statistical signal processing and it is pervasively used in pattern recognition and dimensionality reduction, etc. [26]. By transforming the original dataset into PCA domain and preserving only the several most significant principal components, the noise and trivial information can be removed. In [21], a PCA-based scheme was proposed for image denoising by using a moving window to calculate the local statistics, from which the local PCA transformation matrix was estimated. However, this scheme applies PCA directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs.

In the proposed SSS-PCA, we model a pixel and its nearest neighbors as a vector variable. The training samples of this variable are selected by identifying the pixels with self similarity based local spatial structures to the underlying one in the local window. With such an SSS procedure, the local structural 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 removal. As shown in Fig. 1, the proposed SSS-PCA algorithm has two stages. The first 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 SSS accuracy will be much improved in the second stage so that the final denoising result is visually much better. The proposed SSS-PCA method provides proper definition of the structure of the

Manuscript received May 5, 2011
Manuscript revised May 20, 2011

image so that it can better characterize the image local structures.
The rest of the paper is structured as follows. Section 2 briefly reviews the procedure of PCA. Section 3 presents the SSS-PCA denoising algorithm in detail and Section 4 concludes the paper.

## 2. PCA-BASED DENOISING OF MOSAIC IMAGES

Let the image matrix can be defined by X matrix which can be given as

1

Where the ith row can be given as

#

2

is called the sample vector of Xi. The mean value of Xi is calculated as

3

and then the sample vector Xi is centralized as

#

4

The centralized matrix of X is

5

Finally, the co-variance matrix of the centralized dataset is calculated as

6

The goal of PCA is to find an orthonormal transformation matrix P to de-correlate , i.e. so that the co-variance matrix of is diagonal. Since the co-variance matrix $\bar{X}$ is symmetrical, it can be written as:

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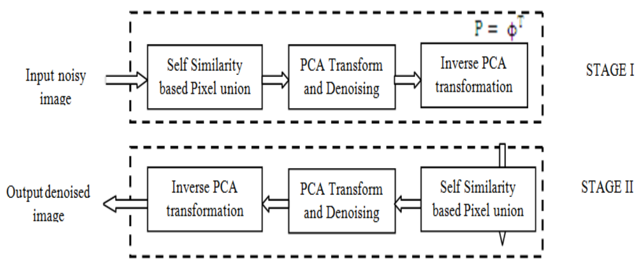


Where

is the m x m orthonormal eigenvector matrix. . is the diagonal eigenvalue matrix. By using the above value we can calculate the P value which can be given as:

By using P, the can be decorrelated and therefore, the signal and noise can be better distinguished in the PCA domain.

## 3. SSS-PCS DENOISING ALGORITHM

The optimal dimension reduction property of PCA can be used to reduce noise. By computing the covariance matrix ω of x , the optimal PCA transformation matrix the optimal PCA transformation matrix P for x can be obtained. However, the available dataset X is noise corrupted so that ω cannot be directly computed. Fortunately, ω can be estimated using the linear noise model. Assuming that n training samples are available for each element of the covariance matrix of $X$ can be estimated using maximal likelihood estimation (MLE). The goal of denoising is to obtain estimation, denoted by of X from the observation $X_v$. The denoised image $X_v$ is expected to be as close to X as possible.
An image pixel is described by two quantities, the spatial location and its intensity, while the image local structure is represented as a set of neighboring pixels at different intensity levels. Since most of the semantic information of an image is conveyed by its edge structures, edge preservation is highly desired in image denoising. To this end, in this paper we model a pixel and its nearest neighbors as a vector variable and perform noise reduction on the vector instead of the single pixel.

Since the observed image is noise corrupted, we denote by

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We use an (L>K) training block centered on $X_v$ to find the training samples. The simplest way is to take the pixel as in each possible block with in the training block as the samples of noisy variable $X_v$. In this way, there are totally (L-K+1)2 training samples for each component of $X_v$. However, there can be very different blocks from the given central block in the training window so that taking all the blocks as the training samples of $X_v$ will lead to in accurate estimation of the covariance matrix of $X_v$, which subsequently leads to in accurate estimation of the PCA transformation matrix and finally results in much noise residual Therefore, selecting and grouping the training samples that similar to the central. block is necessary before applying the PCA transform for denoising.

## 3.1 Self Similarity Pixel Strategy

This algorithm takes advantage of image self-similarity to recreate textures from small samples. By comparing the image with itself, it recovers missing values by transporting them from places where they are known. The assumption underlying the proposed demosaicking algorithm is the following:

*Color information present in the raw image is redundant, and can be transported from pixels where it is known to pixels where it is missing based on local similarities.*

A similar principle has already be briefly tested for demosaicking. Mairal et al. [22] proposed to adapt to demosaicking a denoising and in painting algorithm based on a sparse representation obtained from a learned dictionary of image patches. They obtained excellent demosaicking results on some examples by this completely non-local strategy. The method is nonetheless rather a demonstration of the power of K-SVD classification and sparse representations, than a realistic demosaicking algorithm. Indeed, the dictionary must be learned for each image.

The $K \times K$ block comparison permits a reliable similarity measure involving pixels which can fall far away from each other This permits a non-local strategy and the systematic use of all possible self-predictions the image can provide, in the spirit of Efros and Leung [19]. The block comparison also makes weight distributions in the mean computing the denoised value adapt to the local geometry of the image. The process of averaging pixels is a way to reduce oscillations due to noise, and the value of the resolution parameter h depends on the noise standard deviation. The window distances are computed on the initial estimate u0

$$M[u](x) = \frac{1}{C(x)}\int_{\omega} e^{-\frac{1}{h^2}\int_{R^2} G_a(t)|u_0(x+t)-u_0(y+t)|^2} \qquad 10$$

where x is the new-interpolated pixel and C(x) is the normalization factor. If the initial guess u0 has several artifacts or erroneous structures (which it is usually the case), then looking for similar pixels and copying their grey level values can lead to the reinforcement of these artifacts. For this reason, the algorithm is coarse to fine. It first reconstructs the large scale structures and iteratively refines the search by reducing the value of h.

## 3.2 SSS-PCA based Denoising

By computing the covariance matrix of X, denoted by Xx, the PCA transformation matrix P can be obtained. However, the available dataset Xv is noise corrupted so that $\omega$ cannot be directly computed. With the linear model we have

$$\omega = \frac{1}{n}\bar{X}\bar{X}^T = \frac{1}{n}XX^T + XV^T + VX^T + VV^T \qquad 11$$

Since the signal $\bar{X}$and noise V are uncorrelated, items XVT and VXT will be nearly zero matrices which reduce the above expression of to the following:

$$\omega = \frac{1}{n}\bar{X}\bar{X}^T \approx \frac{1}{n}(XX^T + VV^T) \qquad 12$$

Where $\omega_x = \frac{1}{n}\bar{X}\bar{X}^T$ and $\omega_v = \frac{1}{n}\bar{V}\bar{V}^T$

The orthonormal PCA transformation matrix for X is set as

$$P_x = \Phi_x^T \qquad 13$$

Applying Px to dataset Xv, we have

$$Y_v = P_x X_v = P_x X + P_x V = Y + V \qquad 14$$

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where $Y = P_x X$ is the decorrelated data set for X and is $V_Y = P_x V$ the transformed noise data set for V. Since Y and noise VY are uncorrelated, we can easily derive that the covariance matrix of Yv is

$$\omega = \frac{1}{n} Y_v Y_v^T \qquad 15$$

In the PCA transformed domain $Y_v$, most energy of noiseless dataset Y concentrate on the several most important components, while the energy of noise $V_y$ distributes much more evenly. The noise in $Y_v$ can be suppressed by using the linear minimum mean square-error estimation (LMMSE) technique. Since $Y_v$ is centralized, the LMMSE of $Y_k$, i.e. the kth row of Y, is obtained as

$$Y_k = \gamma_k Y_v^k \text{ where } \gamma_k = \frac{\omega_x(k,k)}{\omega_y(k,k)} + \omega_{V_y}(k,k) \qquad 16$$

Here most of the noise will be suppressed in Y,k by LMMSE operator $Y_k = \gamma_k Y_v^k$

In implementation we first calculate $\omega_y$ from the available noisy dataset Yv and then estimate

$$\omega_x(k,k)/\omega_x(k,k) = \omega_Y(k,k) - \omega_v(k,k) \qquad 17$$

Since the equation 17 will provide value almost equal to zero In this case $k_k$ will be exactly and all the noise in $Y_v$ at kth row will be removed.

### 3.2.1 Denoising refinement in the second stage

Most of the noise will be removed by using the denoising procedures describe in 3.2.However; there is still much visually unpleasant noise residual in the denoised image.

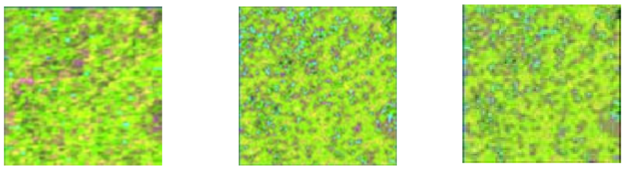
There are mainly two reasons for the noise residual. First, because of the strong noise in the original dataset $V_T$, the covariance matrix $V_T$ is much noise corrupted, which leadst o estimation bias of the PCA transformation matrix and hence deteriorates the denoising performance; second,the strong noise in the original dataset will also lead to SSS errors, which consequently results in estimation bias of the covariance matrix $V_T$ (or $V_T$ ). Therefore, it is necessary to further process the denoising output for a better noise reduction. Since the noise has been much removed in the first round of SSS-PCA denoising, the SSS accuracy and the estimation of $V_T$ (or $V_T$ ) can be much improved with the denoised image. Thus we can implement the SSS-PCA denoising procedure for these condintional round to enhance the denoising results.

3.2.2 Denoising of color images

There are two approaches to extending the proposed SSS-PCA algorithm to color images. The first approach is to apply separately SSS-PCA to each of the red, green and blue channels. This approach is simple to implement but it ignores the spectral correlation in the color image. The second approach is to form a K x K x 3 color variable cube with each K x K variable block corresponding to the red, green or blue channel. Then the training samples of the color variable vector are selected in the local L x L x 3 window using the SSS procedure. All the other steps are the same as those in the SSS-PCA denoising of grey level images. Compared with the first approach, this conditional approach can exploit both the spatial correlation and the spectral correlation in denoising color images. However, there are two main problems. First, the dimensionality of the color variable vector is three times that of the gray level image, and this will increase significantly the computational cost in the PCA denoising process. Second, the high dimensionality of the color variable vector requires much more training samples to be found in the SSS processing. Nonetheless, we may not be able to find enough training samples in the local neighborhood so that the covariance matrix of the color variable vector may not be accurately estimated, and hence the denoising performance can be reduced.

## 4. Experimental Result

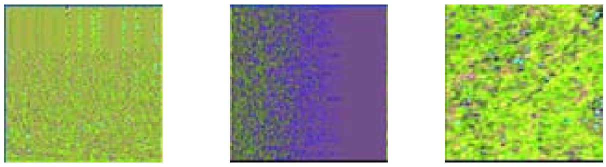
To validate our proposed Two stage Denoising scheme, we tested it on a large public mosaic images[12]. The database contains large collection of grayscale images. We apply our algorithm to the images to obtain more effective denoised images. The image size has been defined in the range of 128 x 128 so as to make image denoising at low level.



(a) (b) (c)

Figure 2: In the Figure , (a) Noised Raw Image , (b) Denoised raw image using Leeflit method and (c) denoised raw image using proposed Scheme.

The raw image has been processed through various steps to obtain the effectively denoised image. These include PCA based important image information, removal of noising through nearest neighbor comparison etc.



(a) (b) (c)

Figure 3: It shows the various stage based image that can be defined through (a) Eigen vectored based image, (b) Inverted PCA based image and (c) Denoised non Smoothed image.

These shown results are further processed to obtain clear cut view of edge based distinction and the result of the existing method and proposed method have defined variation to define the edge of the image content.

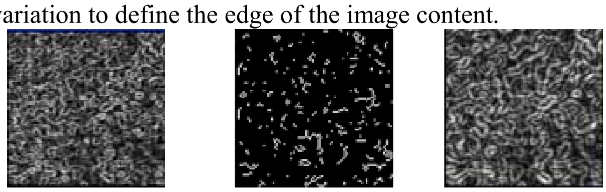
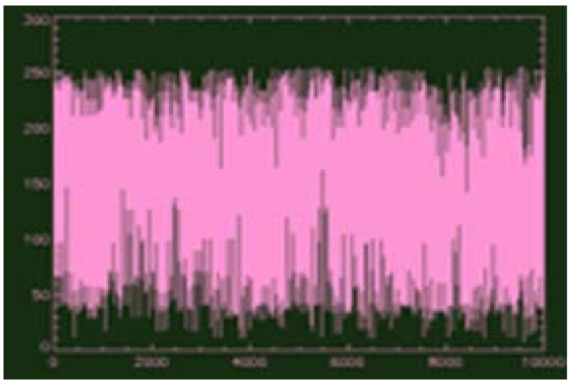


Figure 4: It shows the clear view of edge enhancement in the denoised image.

The frequency distribution of the denoised image can be given as:



## 5. Conclusion

This paper proposed a 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 .A training sample selection procedure is necessary. The block matching based self similarity scaled (SSS) 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 SSS-PCA denoising procedure was iterated one more time to improve the denoising performance. SSS-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.

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