PRINCIPAL COMPONENT ANALYSIS IMAGE DENOISING USING LOCAL PIXEL GROUPING

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ABSTRACT

In recent years various image processing techniques have been developed. These include medical, satellite, space, transmission and radar etc. But noise in image effect all applications. So it is necessary to remove noise from image. There are various methods and techniques to remove noise from images. Wavelet transform (WT) is effective in noise removal but it has some limitations that are overcome by PCA method.

For image denoising a Principal component analysis (PCA) based scheme is proposed by using a moving window to calculate the local statistics, from which the local PCA transformation matrix is estimated. PCA is applied directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs.

***Keywords:* PCA, WT, LPG**

I. INTRODUCTION

A very large portion of digital images processing is devoted to restoration. Image restoration is the reduction of degradations that are incurred while the image is obtained. Degradation comes from blurring as well as noise due to electronics and photometric sources.[1] A noisy channel introduce noise in the transmission medium, error may be during the measurement process and during quantization of the data. Each element contributes to the degradation in the imaging chain such as lenses, film, digitizer, etc.[2]

Image denoising is often used in the field of image processing where an image was somehow degraded but needs to be improved. “We need to know something about the degradation process in order to develop a model for it. When we have a degradation process model, to restore the image inverse process can be applied. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensates for distortion in the optical system of a telescope” [3]. Image denoising finds application in the field as astronomy where the resolution limitations are severe, in medical imaging, the physical requirement for high quality imaging are needed for analysing images of unique event, and in forensic science sometimes the bad quality photograph may have potentially useful evidence.

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II. PRINCIPAL COMPONENT ANALYSIS

Principle Component Analysis is a statistical analytical tool. It takes a large number of interrelated variables and transforms this data into a smaller number of uncorrelated variables while retaining maximal amount of variation. These uncorrelated variables are known as principal components. "PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analysing data." [7]

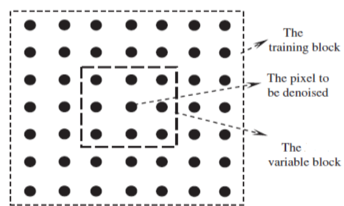

Fig.1. Model of PCA based Denoising Using LPG

A pixel and its nearest neighbours are selected as a vector variable as shown in figure 1. The training sample of this variable is selected by grouping the pixel with similar local spatial structure.

III. LPG PCA DENOISING ALGORITHM

For a better preservation of image local structures, a pixel and its nearest neighbours are modelled 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.

This proposed LPG-PCA algorithm consists of 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 first stage output.

In PCA-LPG based image denoising method most of the computational cost spends on LPG grouping and PCA transformation and thus complexity mainly depends on two parameters: the size of k of variable block and size L of training block.

The first step is to select any image; it may be coloured or gray-scale image. Then we will add noise of our choice, preferably additive Gaussian noise. You may also add salt and pepper noise. Then we will employ local pixel grouping method followed by principal component analysis algorithm. The output of this first stage is the

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input of second stage. Again local pixel grouping method followed by principal component analysis algorithm is applied, as shown in figure 1.

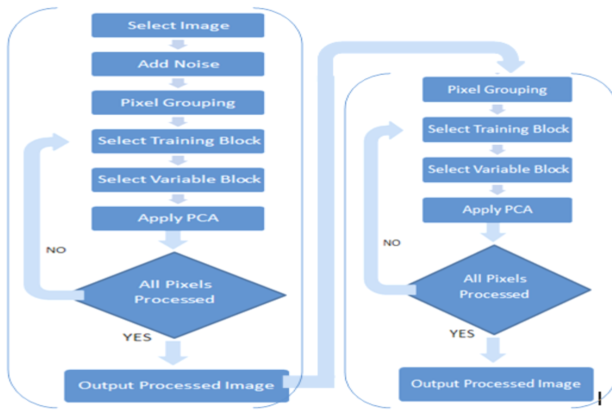

Figure 1: Two Stages of LPG - PCA Algorithm

The parameter of noise level will be different in both the stages. Accuracy will be much improved in the second stage as noise is significantly reduced in the first stage. The final denoised image will be visually much better.

IV. RESULTS

- Image corrupted with salt and pepper noise, p(salt)=0.05 and p(pepper)=0.02
- Image corrected using mean filter.

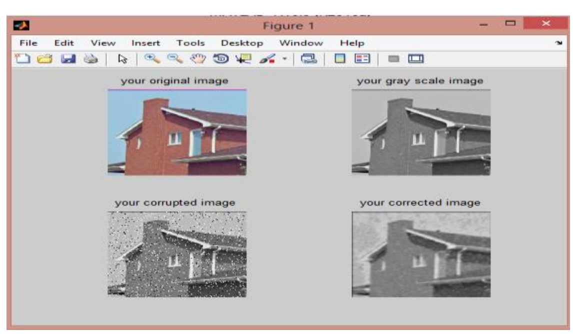

Figure 2: Mean Filter Results

- Image corrupted with Gaussian noise, mean=0.2 and standard deviation=20
- Image corrected using median filter.

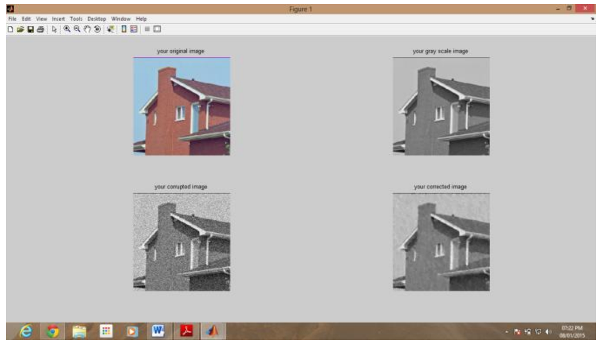

Figure 3: Median Filter Results

- Image corrupted with Gaussian noise, mean=0.2 and standard deviation=20
- Image corrected using Discrete Wavelet Transform.

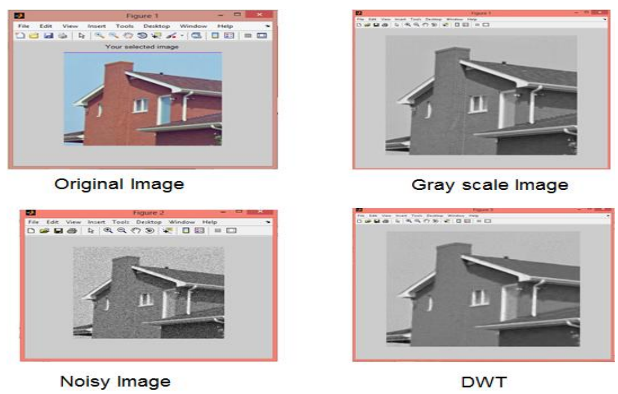

Figure 4: Discrete Wavelet Transform Results

- Image corrupted using Gaussian noise, mean=0.2 and standard deviation=20
- Image corrected using two stage LPG-PCA.

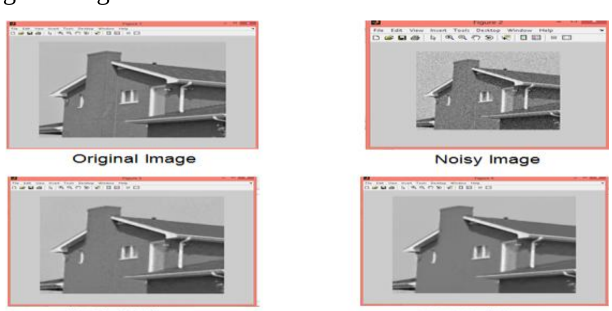

Figure 6: LPG-PCA Results

- PSNR Value Comparison

Table 1: Comparison of PSNR values of different filters

	Monarch	Cameraman	House
Median	20.6154	20.8301	28.5012
Mean	25.2337	24.3735	28.3971
DWT	28.0575	28.3796	31.2737
PCA 1st Stage	29.6746	29.4875	32.1877
PCA 2nd Stage	30.0384	29.7061	33.0613

V CONCLUSIONS

Principal Component Analysis (PCA) reduces the dimensionality of the data while retaining most of the information. This reduction is accomplished by identifying principal components, along which the variation in the data is maximal. By few components, each sample can be represented by relatively few numbers instead of by values for numbers of variable. Samples can then be plotted, making it possible to visually assess similarities and differences between samples and determine whether samples can be grouped.

In this way we proposed a spatially adaptive image denoising scheme by using principal component analysis (PCA). To preserve the local image structures when denoising, we modelled 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.

Local pixel grouping (LPG) uses the block matching technique and it guarantees that only the similar sample blocks are used in the PCA transform matrix estimation. The PCA transformation coefficients were then compressed to remove noise. One more iteration of LPG-PCA denoising procedure was used to improve the performance. Our experimental results demonstrated that LPG-PCA can effectively preserve the image fine structures while smoothing noise.

VI. FUTURE SCOPE

PCA is applied in a lot of others sector such as computer science, image pattern, finding common features of facial images of human beings, image compression and computation biology . Many applications such as classification and clustering have taken advantage of this decomposition. Applications include identifying patterns, estimating missing data, expression patterns and associating genes helping to uncover the dynamic architecture of cellular phenotypes.

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