International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
www.ijset.com, Volume No.1, Issue No.2 pg:22-26 01 April 2012

Image De-noising by Common Vector Elimination in PCA (Principal Component Analysis)

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Abstract: This paper presents the PCA (Principal Component Analysis) based algorithm for noise removal from noisy images, the concept is based on analysis which states that the noise components affects all parts of image uniformly, the noise can be from many independent components, in proposed algorithm the noisy vector is searched on the basis of global similarity of vectors of each segments from the images. The proposed algorithm simulated on MATLAB 7.5 and the results shows that the algorithm works well for de-noising with faster than the other wavelet based PCA methods.

Keywords: PCA (Principal Component Analysis), image de-noising.

1. Introduction

Image de-noising is a vivid research subject in signal processing because of its fundamental role in many applications. With the rapid development of modern digital imaging devices and their increasingly wide applications in our daily life, there are increasing requirements of new de-noising algorithms for higher image quality.

In the past few years, image de-noising has been deeply impacted by a new approach,instead of processing each pixel individually; it has been shown to be preferable to de-noise the image block-wise. Taking advantage of the redundancy of small sub-images inside the image of interest, new robust methods have emerged that can properly handle constant, geometric and textured areas.

There are several de-noising proposals are already available but limitation of processing power and resources availability like power, memory, etc. it is required to develop a new technique which will be capable of doing this work under limited resources.

The proposed technique is a way for such systems here the complicated frequency and mixed domain transformation is avoided to reduce the complexity of the algorithm without compromising with the de-noising performance. The rest of the paper is arranged as that the 2nd section a discussion on recently proposed works on same topic is done. The 3rd section explains the basic of PCA after that 4th section presents the proposed algorithm followed by simulation results and conclusion in 5th and 6th section.

2. Literature Review

A comprehensive review of the literature on image restoration and de-noising is not necessary for this paper. Hence this section only gives a brief summary of the closest related work. One approach to image de-noising proposed by Lei Zhang, David Zhang et al., in their paper "Two-stage image de-noising by principal component analysis with local pixel grouping" [1], This paper presents an efficient image de-noising 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 neighbours 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 de-noising procedure is iterated one more time to further improve the de-noising 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 de-noising performance, especially in image fine structure preservation, compared with state-of-the-art de-noising algorithms. Another analysis is proposed by Tolga Tasdizen in the paper titled "Principal Neighborhood Dictionaries for Non-local Means Image De-noising", they present an in-depth analysis of a variation of the Non-local Means (NLM) image de-noising algorithm that uses principal component analysis (PCA) to achieve a higher accuracy while reducing computational load. Image neighborhood vectors are first projected onto a lower-dimensional subspace using PCA. The dimensionality of this subspace is chosen automatically using parallel analysis. Consequently, neighborhood similarity weights for de-noising are computed using distances in this subspace rather than the full space. The resulting algorithm is referred to as Principal Neighborhood Dictionary (PND) Non-local Means. It also investigate PND's accuracy as a function of the dimensionality of the projection subspace and demonstrate that de-noising accuracy peaks at a relatively low number of dimensions. The accuracy of NLM and PND are also examined with respect to the choice of image neighborhood and search window sizes. Finally, it presents a quantitative and qualitative comparison of PND vs. NLM and another image neighborhood PCA-based state-of-the-art image de-noising algorithm.

Several other relevant works and several produce are presented with very impressive results, such as non-local mean [2], BM3D [6]. All these methods are built upon the same observation that local image patches are often repetitive within an image. Similar patches in an image are grouped together and "collaboratively" filtered to remove noise. While these methods have different algorithmic details, their performance is comparable. Although there is no theoretic proof, we conjecture that the performance limit of single-image de-noising has probably been reached. One approach to break this limit is to use more input images, such as video de-noising. To exploit redundant data in a video, similar patches need to be matched over time for noise removal. Another way of leveraging more input images is to reconstruct a clean image from noisy measurements from multiple viewpoints, proposed by P. Chatterjee and P Milanfar [7]. Only image redundancy across viewpoints is exploited in [7], and patch similarity within individual images is however neglected. In [6], A Buades and B. Coll proposed to combine NL-mean de-noising with binocular stereo matching, therefore exploiting data redundancy both across views and within each image. Coll's main idea is to apply NL-mean to both left and right images and then use the estimated depth to average the two de-noised images.

3. Principal Component Analysis

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

PCA was invented in 1901 by Karl Pearson. Now it is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores (the transformed variable values corresponding to a particular data point) and loadings (the weight by which each standardized original variable should be multiplied to get the component score).

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

PCA is closely related to factor analysis; indeed, some statistical packages deliberately conflate the techniques. True factor analysis makes different assumptions about the underlying structure and solves eigenvectors of a slightly different matrix. PCA can be considered as a type of low-rank approximation.

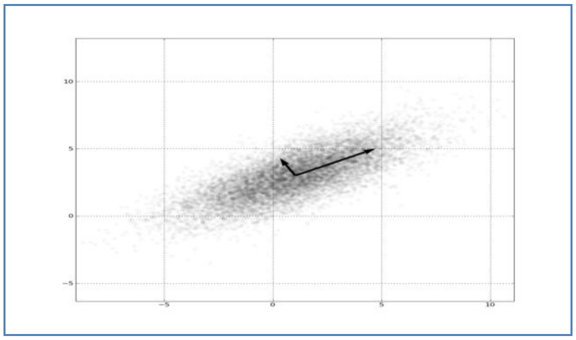

Figure 1: A scatter plot of samples that are distributed according to a multivariate (bivariate) Gaussian distribution centered at (1, 3) with a standard deviation of 3 in roughly the (0.878, 0.478) direction and of 1 in the orthogonal direction. The directions represent the Principal Components (PC) associated with the sample.

4. Proposed Algorithm

The algorithm works on block basis hence the image is firstly sub divided into a block size of NxN overlapping blocks (half-overlap). As shown in figure below

1	**1,2**	**1,2**	**2**			
1,m	**1,2,m**	**1,2,m**	**2**			
1,m	**1,2,m**	**1,2,m**	**2**			
m	**m**	**m**				

Figure 2: Extracting Blocks from image showing overlapping scheme here 1, 2 and m are the pixels associated with that block number for N=3.

After extracting the block each block is converted into a single row vector by shifting each row left of other as shown below.

1	2	3
4	5	6
7	8	9

1	2	3	4	5	6	7	8	9

Figure 3: conversion of block into vector

Now the calculation for Principal Component Vectors is performed for each block. This operation provides NxN vectors for NxN size block.

In next step the vectors of minimum importance (last three) from each block are arranged.

The arrange vectors are now clustered and the radius of each cluster are compared.

Now the vectors which are grouped with minimum radius are marked as noise vectors and the elements related to those vectors are eliminated in each block.

Then the inverse is performed to get the de-noised image.

5. Simulation Results

The above algorithm is performed using MATLAB 7.5 on IBM Pentium 4, 2.4 GHz based processor with 2 GB of RAM. Following results are obtained by the simulation.

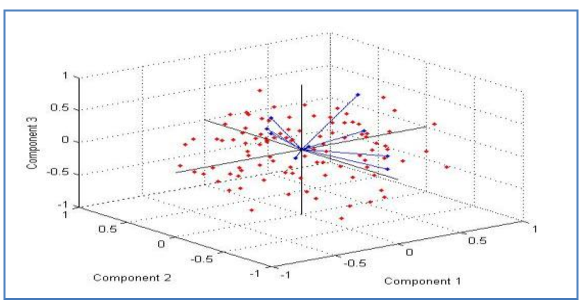

Figure 4: The plot of data points and the vectors in three dimensional space.

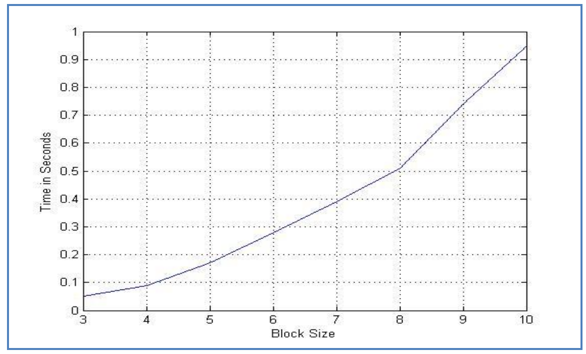

Figure 5: processing time variation with respect to different block size.

Figure 6: Original image Cameraman Left, noisy image (PSNR = 21.7 dB), (SSIM = 0.8443) Right.

Figure 7: De-noised image by the proposed method (PSNR = 29.3 dB), (SSIM = 0.9213).

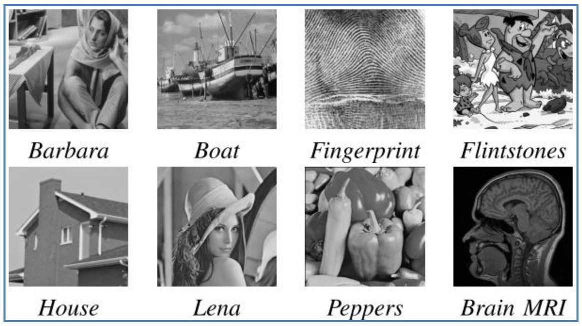

Figure 8: other images used in simulation.

Image	PSNR Before	PSNR After
Barbara	22.4	28.9
Boat	21.3	28.4
Fingerprint	20.1	25.8
Flintstones	23.1	29.3
House	22.7	28.1
Lena	21.9	29.2
Peppers	22.4	28.4
Brain MRI	20.3	27.2

Table 1: Table for PSNR (in dB) results simulated for images shown in Figure 8.

Image	SSIM Before	SSIM After
Barbara	0.8454	0.9411
Boat	0.8233	0.9324
Fingerprint	0.8102	0.8966
Flintstones	0.8509	0.9593
House	0.8327	0.9435
Lena	0.8109	0.9563
Peppers	0.8457	0.9343
Brain MRI	0.8318	0.9412

Table 2: Table for SSIM (Structural Similarity Measurement) results simulated for images shown in Figure 8.

6. Conclusion

This paper proposed a Fast and Efficient image de-noising scheme by using principal component analysis (PCA). The propose technique also having advantage that is does not produce much artifacts on image hence preserve the local image structures when de-noising, our experimental results demonstrated that propose technique effectively preserve the image fine structures while smoothing noise. It presents a competitive de-noising solution compared with other complex de-noising techniques.

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