PCA Based Image Enhancement in Wavelet Domain

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***Abstract*—This paper demonstrates a methodology of image enhancement that uses principle component analysis (PCA) in wavelet domain. PCA fully de-correlates the original data set so that the energy of the signal will concentrate on the small subset of PCA transformed dataset. The energy of random noise evenly spreads over the whole data set, we can easily distinguish signal from random noise over PCA domain. It consists of two stages: image enhancement by removing the random noise and further refinement of the first stage. The random noise is significantly reduced in the first stage; the Local Pixel Grouping (LPG) accuracy will be much improved in the second stage so that the final enhancement result is visually much better. The LPG-PCA enhance procedure is used to improve the image quality from first stage to second stage with edge preservation.**

The wavelet thresholding methods used for removing random noise has been researched extensively due to its effectiveness and simplicity. However, not much has been done to make the threshold values adaptive to the spatially changing statistics of images. Such adaptivity can improve the wavelet thresholding performance because it allows additional local information of the image (such as the identification of smooth or edge regions) to be incorporated into the algorithm.

We compare this two-stage process with traditional principal component analysis and find that the results of the new structure are closer to the structure of traditional quality of image, its purity and descriptors than traditional principal component analysis.

***Keywords*—Wavelet, Wavelet Transform (WT), Local Pixel Grouping (LPG), Principal Components Analysis.**

I. INTRODUCTION

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.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.The LPG algorithm 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 random noise. The LPG-PCA enhancement procedure is iterated one more time to further improve the enhancement 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 enhancement performance, especially in image fine structure preservation, compared with enhancement algorithms.

PCA is the 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 analyzing data. The other main advantage of PCA is that once you have found these patterns in the data and you compress the data i.e. by reducing the number of dimensions without much loss of information. This technique used in image compression. To improve the image quality image enhancement is a essential step. As a primary low-level image processing procedure, random noise removal has been extensively studied and many enhancement schemes have been proposed, from the earlier smoothing filters and frequency domain denoising methods [1] to the lately developed wavelet [2],[3],[11], curvelet [12] and ridgelet [13] based methods, sparse representation [14].With the rapid development of modern digital imaging devices and their increasingly wide applications in our daily life, to overcome the problem with conventional WT [15] we use wavelet PCA. Wavelets are an efficient and practical way to represent edges and image information at multiple spatial scales. Image features at a given scale, such as houses or roads, can be directly enhanced by filtering the wavelet coefficients. Wavelets may be a more useful image representation than pixels. Hence, we consider PCA dimensionality reduction of wavelet coefficients in order to maximize edge information in the reduced dimensionality set of images. The wavelet transform will take place spatially over each image band, while the PCA transform will take place spectrally over the set of images. Thus, the two transforms operate over different domains. Still, PCA over a complete set of wavelet and approximation coefficients will result in exactly the same eigenspectra as PCA over the pixels.

To overcome the problem of WT, in [16] 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 [14],[17] proposed sparse redundant representation and (clustering -singular value decomposition)K-SVD based denoising algorithm by training a highly over-complete dictionary. Foi et al. [18] 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.

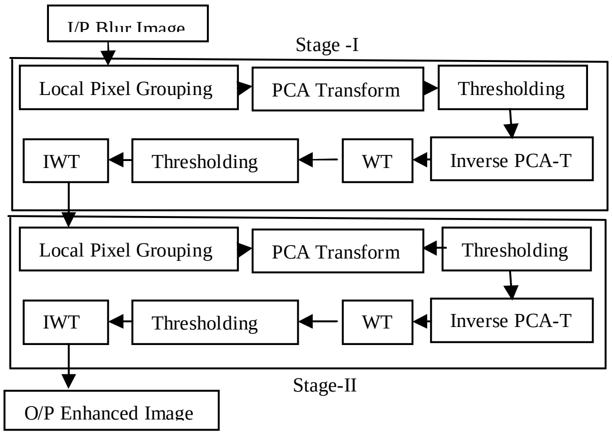

Fig. 1 Block diagram of proposed technique

The system fig.1 algorithm has two stages. In the first stage we give an input as a blur image then apply algorithm Local Pixel Grouping then performs the principal component analysis (PCA) on the blur image. The output from PCA is the eigenimage and the eigenvectors. Apply soft thresholding on a PCA component, the number of them can be selected by the user, and the reconstruction quality in the inverse PCA (IPCA) depends on that number. The eigenimages and the eigenvectors are entropy coded. Then the wavelet transform (WT) is applied to that residual. Then apply thresholding on wavelet coefficient and the reconstruction quality in the Inverse Wavelet Transform (IWT). And get the output enhanced image, and the second stage will further refine the output of the first stage.

The rest of the paper is structured as follows. Section II presents discussion of procedure of PCA. Section III Wavelets transform .Section IV Implementation paper. Section V briefly reviews the experimental results. Section VI Concludes the paper.

II. Principle Component Analysis

PCA [19], [20] is a classical de-correlation technique which has been widely used for dimensionality reduction with direct applications in pattern recognition, data compression and random noise reduction. Denoted by $x=[x_1,x_2 ,. . . x_m]^T$ an m-component vector variable and denote by

X= (1)

the sample matrix of x, where x_j^i , j=1,2,..,n, are the discrete samples of variable x_i , i=1,2,..,m. The ith row of sample matrix X, denoted by

= [ ] (2)

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

=– (j) (3)

and then the sample vector X_i is centralized as

= - =[ ] (4)

Where = $-\mu_i$ accordingly, the centralized matrix of X is

= [$]^T$ (5)

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

Ω = – ^{T} (6)

The goal of PCA is to find an ortho-normal transformation matrix P to de-correlate , i.e. =P so that the co-variance matrix of Y is diagonal. Since the covariance matrix X is symmetrical, it can be written as:

Ω = □ ^ (7)

where □ = [ ]

is the m*m orthonormal eigenvector matrix and = diag{$\lambda_1\lambda_2..\lambda_m$}is the diagonal eigenvalue matrix with λ_1>= λ_2 >=……….>=λ_m the terms $ø_1$ $ø_2$ ……. $ø_m$ and the λ1,λ2..λm are the eigenvectors and eigenvalues of X. By setting

P= □ ^{T}

(8)

$\bar{X}$ can be decorrelated.

An important property of PCA is that it fully de-correlates the original dataset X. Generally speaking, the energy of a signal will concentrate on a small subset of the PCA transformed dataset, while the energy of random noise will evenly spread over the whole dataset. Therefore, the signal and noise can be better disting-uished in the PCA domain.

A. Local Pixel Grouping (LPG)

The LPG, for an under lying pixel to be denoised, we set a K*K window centered on it and denote by $x=[x_1\ldots\ldots\ldots x_m]^T$,$m=K^2$,the vector containing all the components within the window. Since the observed image is noise corrupted, we denote by

$X_v=X+v$ (9)

Grouping the training sample similar to the central K*K block in the L*L training window is indeed a classification problem and thus different grouping methods, such as block matching, correlation-based matching , K-mean s clustering, etc, can be employed based on different criteria. Among them the block matching method may be the simplest yet very efficient one. There are totally (L-K+1)2 possible training blocks of x_n in the L*L training window. We denote by ^{V}the column sample vector containing the pixel sin the central K*K block an denote by , i=1,2,…, $(L-K+1)^2$-1,the sample vectors corresponding to the other blocks. Let and , be the associated noise less sample vectors of and and, respectively. It can be easily calculated that

=– - (10)

In above equation we used the fact that noise u is white and uncorrelated with signal. With equation if

e_i < T +2ó^2 (11)

Where T is a preset threshold, then we select $\vec{X}_i^{\,V}$ as a sample vector of X_v.Suppose we select n sample vectors of X_v including the central vector $\vec{X}_0^{\,V}$ For the convenience of expression, we denote these sample vectors as $\vec{X}_0^{\,V} \vec{X}_1^{\,V} \dots \dots \dots, \vec{X}_{n-1}^{\,V}$ The noise less counter parts of these vectors are denoted as $\vec{X}_0$, $\vec{X}_1 \dots \dots \dots$ Error! Bookmark not defined. Error! Bookmark not defined. $\vec{X}_{n-1}$accordingly. The training dataset for x_v is then formed by

$X_y = [\ \vec{X}_0^{\,v}, \vec{X}_1^{\,v}, \dots \dots \dots, \vec{X}_{n-1}^{\,V}\ ]$

The noiseless counterpart of X_v is denoted as

$X = [\ \vec{X}_0^{\,v}, \vec{X}_1^{\,v}, \dots \dots \dots, \vec{X}_{n-1}^{\,V}\ ]$

III. WAVELET

For the wavelet transform, the coefficients at the course level represent a larger time interval but a narrower band of frequencies. This feature of the wavelet transform is very important for image coding. In the active areas, the image data is more localized in the spatial domain, while in the smooth areas, the image data is more localized in the frequency domain. With traditional transform coding, it is very hard to reach a good compromise. The target region (damaged or lost data or object to be removed) information of the image can be divided into two kinds of conditions. The first class, the distribution of the target information of the image is the local and concentration.

Wavelet transform [6],[7],[8] has been used for various image analysis problems due to its nice multi-resolution properties and decoupling characteristics. The proposed algorithm utilizes the advantages of wavelet transforms for image Enhancement. Wavelet transform has been used as a good image representation and analysis tool mainly due to its multi-resolution analysis, data reparability, and compaction and sparsely features in addition to statistical properties [13]. A wavelet function (t) is a small wave, which must be oscillatory in some way to discriminate between different frequencies. The wavelet [4],[5],[10]contains both the analyzing shape and the window. in fig (2) shows by computing the WT of every row of the image. This results in transformed image where the first column contains averages and all other column contains differences. By using standard algorithm computes the WT of every Column. This results in one average value at the top-left corner, with the rest of the top row containing averages of differences, and with all other pixel value transformed into differences.

The original image was processed through a secondary-level wavelet transformation analysis, as illustrated in below Fig (2) the sub bands are denoted by HL and LH respectively .The lower-right sub band, denoted by HH, reflects diagonal image artefacts. Most interesting id the upper-left sub band, denoted by LL, which consists entirely of averages. This sub band is a one -quarter version of the entire image, containing traces of both the vertical ant the horizontal lines.

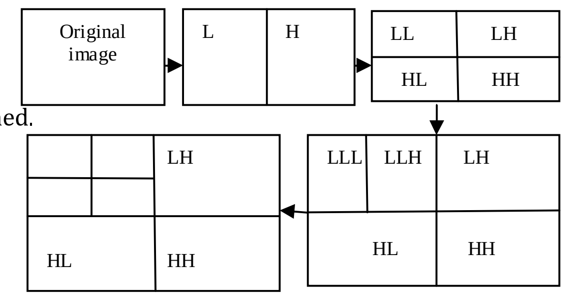

Fig .2 The wavelet transformation analysis derived from various layers of a given image

IV. IMPLEMENTATION

i. Steps for the image enhancement by PCA in wavelet domain are carried out as below.
ii. Apply algorithm of LPG on input blur image.
iii. Do the PCA transform of LPG output image as below.
   a. Get some data.
   b. Subtract the mean.
   c. Calculate the covariance matrix.
   d. Calculate the eigenvectors and eigenvalues of the covariance matrix.
   e. Choosing components and forming a feature vector.
   f. Deriving the new data set.
iv. Apply the soft thresholding of PCA output image.
v. Take inverse PCA.
vi. Do wavelet transform of IPCA output image.
vii. Apply the soft thresholding of wavelet output image.
viii. Take inverse WT.
ix. Apply the output of first stage to input of second stage.
x. Repeat step i to vii
xi. Calculate PSNR for the evaluation of the algorithm.

V. RESULTS

In experimenting result, we try the different experiment to prove the superiority of proposed method. The experimental processes are conducted: it shows Enhancement images. We use the several different characteristic of the images, prove that our Local Pixel Grouping be used provides better results than other existing technique. In order to test the quality of our proposed image Enhancement method, we used various images, including photos, scenery, and artistic compositions. Also we have used different wavelet transforms

Fig. 3 Input image

Fig. 4 Noisy image

Fig.5 Stage –I PCA image

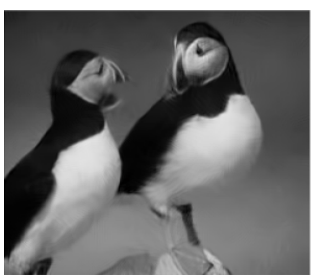

Fig.6 Stage –II PCA image

Fig.7 Wavelet output image

TABLE 1

The PSNR (dB) results of the PCA-based image enhancement in wavelet domain

Different Wavelet Name	PCA Stage-I PSNR(db)	PCA Stage-I PSNR(db)	Wavelet Image PSNR(db)
sym4	18.9052	18.9325	24.5650
db2	18.9052	18.9325	24.8082
harr	18.9052	18.9325	24.6990
coif2	18.9052	18.9325	24.5892
dmey	18.9052	18.9325	24.5285
sym1	18.9052	18.9325	24.5651
db8	18.9052	18.9325	24.8082

VI. CONCLUSION

The principal component analysis is the most famous exploratory method. To preserve the local image structures when Enhancement, we modeled a pixel and its nearest neighbours as a vector variable, and the Enhancement 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.

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