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Image Denoising using Common Vector Elimination by PCA and Wavelet Transform

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ABSTRACT: This paper presents a novel image denoising technique by using Principal Component Analysis (PCA) and Wavelet transform. The noisy image can be decomposed by the PCA into different blocks. Eigen values for each block is calculated and the common vector from each block is eliminated. The noise under consideration is AWGN and is treated as a Gaussian random variable. The denoised image obtained by using the above algorithm is processed again by using wavelet transform. This post processing results in further improvement of the denoised results. Experimental results show better performance in terms of PSNR as compared to the performance of the methods when incorporated individually.

Keywords: Eigen vectors, Image Denoising, Speckle Noise, Wavelet Transform

I. INTRODUCTION

Noise removal is one of the very important aspect in the field of image processing. An image gets distorted with different types of noise during the process of transmission and reception. Noise may be classified as substitutive noise speckle noise and additive white Gaussian noise. Different wavelets techniques are used to remove the level of noise from the Image. However selection of threshold is very important. Principle component analysis (PCA) is a technique used for compression as well as classification of data. The aim is to reduce the dimensionality for a data set there by findig a new set of variables which is smaller than the original set of variables and preserves most of the sample's information. Noise of different variance level has been added and it is passed to wavelet denoising techniques for noise suppression. The proposed algorithm is evaluated in terms of mean square error, peak signal to noise ratio and processing time[1].

II. LITERATURE SURVEY

In this section, recent works provides us some useful information for development of the proposed work. A comprehensive review of the literature on image denoising is beyond the scope of this paper. Here a brief summary of the closest related work has been done. One of the methods is Non Local Means (NLM) image denoising algorithm that uses PCA to obtain higher accuracy. The author proposes quantitative as well as qualitative comparison of NLM and another image neighbourhood PCA based image denoising method [4].The accuracy and computation cost of the NLM image denoising method is improved by calculating neighbouhood similarities after a PCA projection to reduced dimensional space. Another paper proposes a method using contour let transform and 2DPCA. The contourlet transform performs multire solution and multidirectional decomposition to the image, while 2DPCA is carried out to estimate threshold. Proposed method has a better performance than the classical wavelet soft thresholding [1]. Philip Langley [5] proposes another approach for analyzing changes in ECG morphology based on principal component analysis is presented and it is applied to the derivation of surrogate respiratory signals from single-lead ECGs.

The respiratory-induced variability of ECG features, P waves and T waves are described by the PCA. The author has done assessment for which ECG features and which principal components yielded the best surrogate for the respiratory signal. Turgay Celik [8] proposes a new technique for unsupervised change detection in multi temporal satellite images using principal component analysis (PCA) as well as k-means clustering. The image is partitioned into different blocks. Ortho normal Eigen vectors are extracted through PCA of h× h non overlapping block set to create an eigenvector space Simulation results shows that this method performs quite well on combating both the zero-mean Gaussian noise and the other noise, which is quite attractive for change detection in optical and SAR images.

Guangyi Chen [7] proposes a new method for hyperspectral data cubes that have a good signal to noise ratio (SNR). The author proposes to decorrelate the image information of hyperspectral data cubes from the noise by using PCA. A 2D bivariate wavelet thresholding method is used to remove the noise for low energy PCA channels. Sudha *et al.,* [9] presents a wavelet-based thresholding scheme for noise suppression in ultrasound images. Quantitative and qualitative comparisons of the results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction. Ratha Jeyalakshmi and Ramar [10] they described and analyzed an algorithm for cleaning speckle noise in ultrasound medical images. Mathematical Morphological operations are used in this algorithm. This algorithm is based on Morphological Image Cleaning algorithm (MIC). The algorithm uses a different technique for reconstructing the features that are lost while removing the noise. For morphological operations it also uses arbitrary structuring elements suitable for the ultrasound images which have multiplicative noise. Pier rick Coupe's, Pierre Hillier, Charles Kervrann and Christian Barillot [11] proposed a Bayesian Non Local Means-Based Speckle Filtering In their proposal, a new version of the Non Local (NL) Means filter adapted for US images is proposed. Originally developed for Gaussian noise removal, a Bayesian framework is used to adapt the NL means filter for noise. Experiments were carried out on synthetic data sets with different speckle simulations. Nonlocal Means-Based Speckle Filtering for Ultrasound Images is presented by [12]. In this method, an adaptation of the nonlocal (NL) means filter is proposed for speckle reduction in ultrasound (US) images. Originally developed for additive white Gaussian noise, we propose to use a Bayesian framework to derive a NL-means filter adapted to a relevant noise model. Results on real images demonstrate that the proposed method is able to preserve accurately edges and structural details of the image. Bhuiyan *et al.,* [13] presented Wavelet-Based Despeckling of Medical Ultrasound Images with The Symmetric Normal Inverse Gaussian Prior In their proposal, an efficient wavelet-based method is proposed for despeckling medical ultrasound images. A simple method is presented for obtaining the parameters of the SNIG prior using local neighbors. Thus, the proposed method is spatially adaptive. Jeny Rajan and M.R. Kaimal [14] In their paper they discuss the speckle reduction in images with the recently proposed Wavelet Embedded Anisotropic Diffusion (WEAD) and Wavelet Embedded Complex Diffusion (WECD). Both WEAD and WECD produce excellent results when compared with the existing speckle reduction filters. Philip Langley proposed a denoising method for hyper spectral data cubes .Experimental results demonstrated that the proposed denoising methods produces better denoising results in terms of PSNR. Ioana Firoiu, Corina Nafornita [18] proposes the use of a recently introduced hyperanalytic WT (HWT), in association with filtering techniques already used with the discrete wavelet transform. The result is a very simple and fast image denoising algorithm. Lei Zhan & Rastislav Lukac [19] proposes a principle component analysis based spatially-adaptive denoising method, which works directly on Colour Filter Array data using a supporting window to analyze the local image statistics. By using the spatial and spectral correlations existed in the CFA image, the proposed method can effectively suppress noise while retaining color edges and details. Experiments using both simulated and real CFA images indicate that the proposed scheme outperforms many existing approaches, including those sophisticated demosaicking and denoising schemes, in terms of both objective measurement and visual evaluation.

III. PRINCIPAL COMPONENT ANALYSIS

The central idea of Principal Component Analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the Principal Components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables. Principal component analysis 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)[1].

IV. WAVELET THRESHOLDING

Sure shrink method is widely used as orthonormal wavelet transform for wavelet thresholding. The basic method for SURE shrink is to set to zero all coefficients below a particular threshold value T, while shrinking the remaining ones by this same value; this technique is thus also called soft thresholding [3].

$\square(y) = \mathrm{sign}(y)(|y| - T)+$

The soft thresholding function has been shown to be very near to optimal value. The threshold value T is then selected so as to minimize the risk level. The mean squared error (MSE) is the important parameter in image processing . Hence, we can write it as follows:

MSE(Image Domain) $= \frac{1}{N}\sum_{i=1}^{N}(\dot{f}i - fi)^2$ (1)

$= \frac{1}{N}\sum_{j=1}^{j}\sum_{i=1}^{N_j}(\ddot{x}_i^j - x_i^j)^2$ (2)

= MSE (Wavelet Domain)

Where N is the number of samples;
J is the number of channels;
NJ is the number of samples in the channel j.
I is the it sample of the jet channel.

As the non-noisy wavelet coefficients are unknown, we need to estimate the MSE using Stein's unbiased risk estimator (SURE).Its minimization according to our particular estimator ˆx = □(y) leads to:

$SURE_j(t,y) = \sigma^2 - 1/Nj\ (2\ \sigma^2.\#\{i:|yi| <= t\}$
$+ \sum_{i=1}^{Nj} \min\ (|yi|, t^2)$ (3)

The resulting threshold is thus:

T_j = argmin $(SURE_j(t,y))$ (4)

The basic idea of using Prob Shrink method is estimating the probability that a given coefficient contains a significant noise-free component, which we call "signal of interest." In this respect, we analyze cases where the involved probabilities are1) fixed per sub band 2) conditioned on a local spatial context 3) conditioned on information from multiple image bands in case of multi valued images. For actual denoising, the simple shrinkage rule is that where empirical wavelet coefficients are multiplied with the probability of containing a significant noise-free component. We assume the input image is contaminated with signal-independent additive white Gaussian noise of zero mean and variance. An orthogonal wavelet transformation of the noisy input yields an equivalent additive white noise model in the transform domain. In each wavelet subband at a given scale and orientation, we have

$y_i = \beta_i + \epsilon_i$, i= 1.,2,3…..n (5)

where $\beta_i$are noise-free wavelet coefficients, $\epsilon_i$are independent identically distributed (i.i.d.) normal random variables, which are statistically independent fromβ_i and is n the number of coefficients in a subband. For compactness, we suppressed here the indices that denote the scale and the orientation and we denoted the spatial position with a single index, like in a raster scanning. In the remainder of this section, we suppress the spatial index too because the same shrinkage rule will be applied to all the coefficients in a given sub band. Our approach is aimed for priors that are sharply peaked at zero and heavy-tailed like Laplacian, generalized Laplacian and alpha-stable distributions. The generalized Laplacian prior for the noise-free subband data is

$f(\beta) = \frac{\lambda v}{2\Gamma(\frac{1}{v})}\exp\left(-\lambda\beta^v\right)$ (6)

Where $\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt$

where is the Gamma function,$\lambda > 0$ isthe *scale* parameter, and v is the *shape* parameter, which is typically $v \in [0,1]$for natural images. Let us define a "*signal of interest*" as a noise-free coefficient component that exceeds a specific threshold and formulate the following two hypotheses:H_0 , "the signal of interest is absent,"and H_1, "the signal of interest is present" (in a given coefficient),precisely as

$H_0 : |\beta| <= T$ and $H_1 : |\beta| > T$

Let $P(H_1/y)$ denote the conditional probability that a waveletcoefficient contains a signal of interest, given its observed value.The Bayes' rule yields

$P(H_1/y) = \frac{\mu\eta}{1+\mu\eta}$ (7)

Where $\mu = P(H_1)/P(H_0)$ and $\eta = f(y/H_1)/f(y/H_0)$ and the product is called the generalized likelihood ratio [38].We now consider a simple shrinkage rule

$\beta = P(H_1/y)y = \frac{\mu\eta}{1+\mu\eta}\ y$ (8)

This is the equation for Probshrink.

IV. PROPOSED ALGORITHM

Step 1: Firstly divide the noisy image into N equal blocks.
Step 2: Calculate the Principal Components & their Vectors for all the segments.
Step 3: Search for the common (almost similar) vectors in all segments.
Step 4: Create the average vector from all common vectors.
Step 5: Estimate the components in the direction of average common vector for all segments.
Step 6: Remove the above calculated components from the respective segments.
Step 7: Calculate the variance of the components calculated in the step 5.
Step 8: Calculate the optimum threshold for hard and soft thresholding for wavelet domain filtration by using the variance estimated in step 7.

V. 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.

Test Image Pepper is corrupted by Addtive white Gaussian Noise and the plot for PSNR, MSE, Threshold value and Execution time is shown

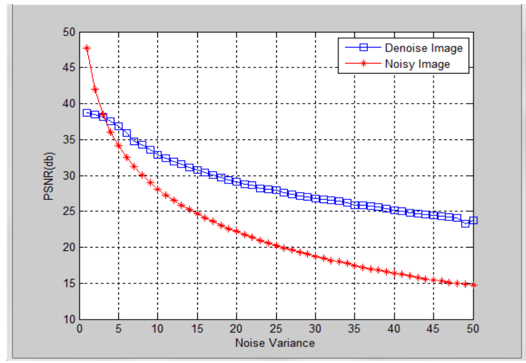

Fig. 1. Plot for denoised image Pepper PSNR for various level of noise variance.

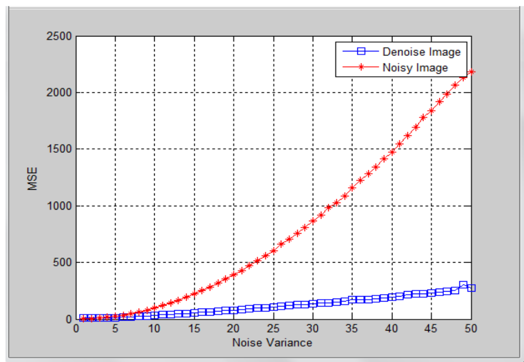

Fig. 2. Plot for denoised image Pepper MSE for various level of noise variance.

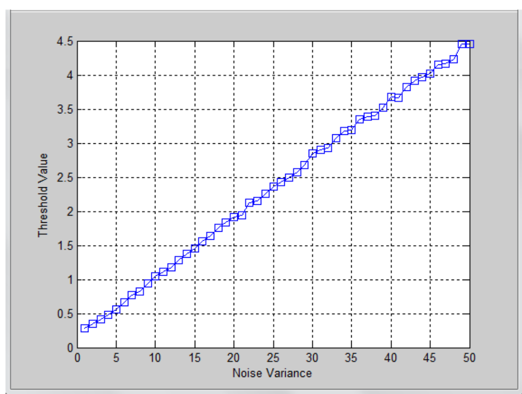

Fig. 3. Plot for denoised image Pepper Threshold value for various level of noise variance.

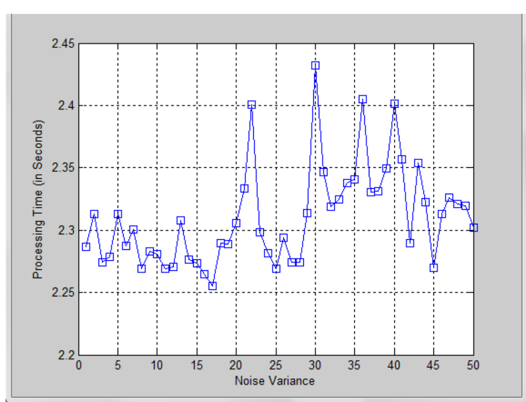

Fig. 4. Plot for denoised image Pepper Execution time for various level of noise variance.

Test Image Barbara is corrupted by Addtive white Gaussian Noise and the plot for PSNR , MSE, Threshold value and Execution time is shown

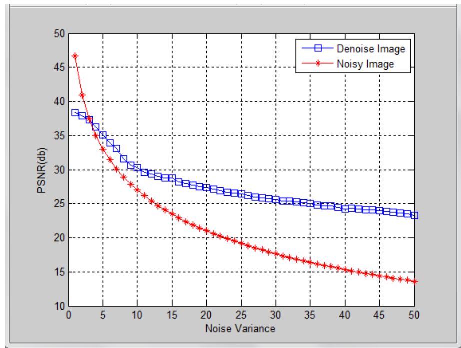

Fig. 5. Plot for denoised image Barbara PSNR for various level of noise variance.

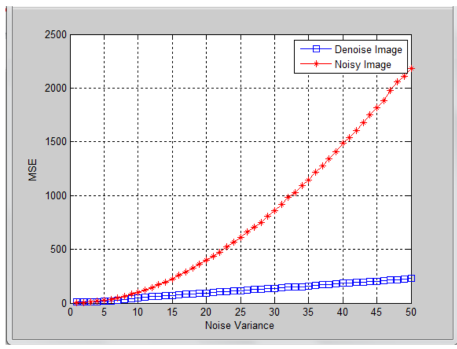

Fig. 6. Plot for denoised image Barbara MSE for various level of noise variance.

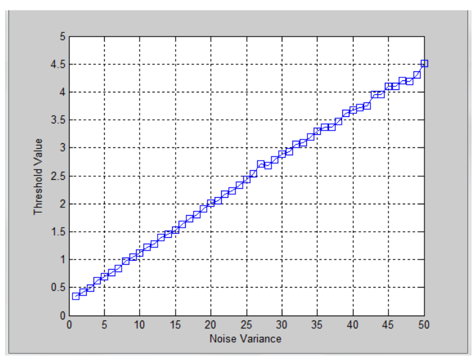

Fig. 7. Plot for denoised image Barbara Threshold value for various level of noise variance.

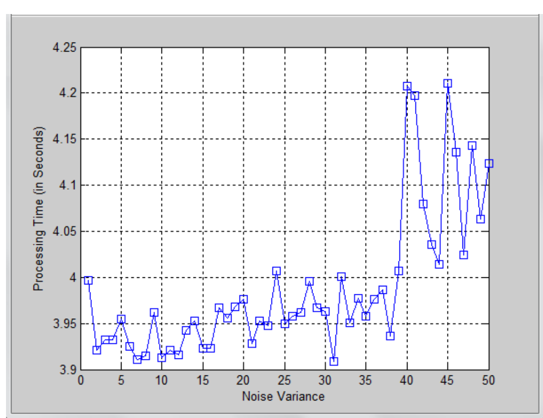

Fig. 8. Plot for denoised image Barbara Execution time for various level of noise variance.

Table1. Comparison of Previous Wavelet technique & Proposed method interms of PSNR (in dB) for Pepper image distorted by AWGN of Different Noise Variance.

.Variance	Noisy Image	Wavelet Transform	Contourlet Transform[1]	CT & 2DPCA[1]	Proposed Method
5	34.25	36.1	36.25	36.35	**37.10**
10	28.15	31.92	31.5	31.96	**33.20**
15	24.6	30.12	29.85	30.36	**30.92**
20	22.1	28.79	28.55	29.20	**29.68**
25	20.17	27.66	27.51	28.16	**28.42**
30	18.9	26.61	26.61	27.55	**27.85**

Table 2: Comparison of Previous Wavelet technique & Proposed method in terms of PSNR (in dB) for Barbara image distorted by AWGN of Different Noise Variance.

.Variance	Noisy Image	Wavelet Transform	ContourletT ransform[1]	CT & 2DPCA[1]	Proposed Method
5	33.25	33.95	34.85	35.05	**35.26**
10	28.15	29.44	29.67	30.34	**30.56**
15	23.6	27.03	27.46	27.90	**28.8**
20	21.1	25.47	26.05	26.05	**27.50**
25	29.17	24.30	24.97	25.90	**26.62**
30	17.9	23.50	24.10	25.11	**25.85**

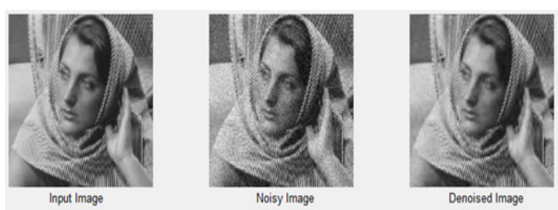

Fig. 9. Denoising results of image Barbara variance = 15.

Fig. 10. Denoising results of image Pepper variance = 15.

Fig. 11. Denoising results of image Boat variance = 15.

Fig. 12. Denoising results of image Lena variance = 15.

Fig. 13. Denoising results of image Cameraman variance = 15.

Fig. 14. Denoising results of image House variance = 15.

VI. CONCLUSION

The values of PSNR for various algorithm are provided in Tables 1 & 2. The proposed Principal Component Analysis and wavelet transform method yields the maximum PSNR values and for various noise levels in comparison to the other wavelet thresholding techniques 2DPCA techniques. The denoising results using Proposed method for different test images under different variance level provides better performance in terms of PSNR, MSE and Execution time as compare to other thresholding techniques.

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