NOISE VARIANCE ESTIMATION OF TEXTURED IMAGES APPLIED FOR BAYESSHRINK DENOISING

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ABSTRACT

Estimation of noise variance is an important parameter in many image processing applications such as denoising, compression, segmentation and edge detection. In this paper, literature survey on techniques of noise variance estimation has been presented and these techniques are compared. It has been observed that most of the estimation methods overestimate the noise variance for rich textured images like baboon, mountain, and grass etc. It is found that PCA based methods gives more accurate estimation in comparison to other methods for textured images. In this work, the PCA based method is applied for noise variance estimation in BayesShrink denoising. It competes well with the MAD based noise variance estimation method adopted in BayesShrink and outperforms in most of the experimental results as presented in this paper. The PCA based method provides a more accurate noise level estimation for low as well as high noise level for all types of images. Also in this work, different noise variance estimation methods are applied to BayesShrink denoising and the results are compared. The experimental result shows that the PCA based method improves the denoising performance of BayesShrink in contrast to other methods especially for textured images.

IndexTerms - Gaussian white noise, BayesShrink, PCA, textured images, image denoising, and noise variance estimation

1. INTRODUCTION

Noise variance estimation is an integrated step in many image processing applications such as image denoising, segmentation, smoothing, and edge detection and so on. The performance of these applications heavily depends on the accuracy of the estimated noise level. Many noise level estimation algorithms have been developed so far, but accurate noise variance estimation for textured images is still a great challenge for researchers in this field. In this work, noise variance estimation for image denoising is considered. Since in many image processing applications such as medical science and astronomy, noise reduction is used as preprocessing step. There are many denoising techniques available in the literature such as bilateral filtering, anisotropic diffusion, median filtering and wavelet based BayesShrink thresholding .It has been found that the methods adopted for the noise variance in these denoising algorithms does not give expected results for textured images. Therefore a robust method for noise level estimation is highly demanded. The most common model adopted universally for noise is additive white Gaussian noise (AWGN) model. The goal of the noise level estimation is to estimate the unknown noise variance or standard deviation given only single observed noisy image. It is assumed that no prior noise variance is supplied to the denoising algorithms in advance.

Generally, noise variance estimation algorithms in spatial domain are classified in to two approaches: filtering based and block or patch based methods. In filtering based methods [1]-[8] a noisy input image is first filtered using a low pass filter and then the standard deviation of the difference image that is computed between noisy and the filtered image is taken as the output noise standard deviation. The disadvantage of this method is that it overestimates the noise level in textured images since filtering leads to smoothing of fine details in addition to noise in the images. Some of the filtering based methods [1] also require a high computational load and large amount of memory. In block based methods [9]-[11], the input noisy image is decomposed in certain size blocks and the local variance of each block is computed. It is considered that the variation of intensity in homogenous blocks is mainly due to noise in those blocks and hence the local variance of the most homogenous block is taken as the output noise variance. The block based method is simple and effective but it tends to overestimate and underestimate the noise level in case of low and high noise in input noisy image. In transform based methods [12]-[15], the noise variance is estimated through median absolute deviation (MAD) method. This approach uses the finest decomposition level wavelet coefficients i.e. HH1 subband for noise level estimation. This method assumes that the HH1 subband coefficients are only associated with noise and thus overestimates the noise level for textured images. After an exhaustive research on noise estimation methods that are discussed in next section, it is found that principal component analysis (PCA) based method is most appropriate for noise estimation in textured images. The performance of surveyed noise level estimation methods are tested by integrating it in BayesShrink denoising technique of image noise reduction. The methods are sequentially applied in the denoising algorithm to estimate the noise level and later on their effect on denoising performance are compared with the help of simple as well as textured images. The superiority of the PCA based method is clearly visible from the denoised images shown and statistical values tabulated.

This structure of the paper is as follows: Literature survey on the noise variance estimation methods is shown in sention-II.PCA based noise level estimation method is shown in section III. BayesShrink denoising approach is described in section IV and the experimental results are tabulated and discussed in section-V. The paper is concluded in section-VI.

2. LITERATURE SURVEY

Noise level estimation is required in before hand to apply the denoising techniques to noisy images. Many approaches of noise level estimation given in research papers are reviewed and the proposed methods are discussed in this section. Many of these estimation algorithms generally follow the approach of separating signal and noise from the input noisy image. In [10] homogenous areas are classified, since the variance in these areas is generally due to noise present in these regions. In [1], [3], the noisy image is convolved with the high pass filter and the difference between the filtered and the noisy image is computed. The difference image mainly contains the edge and the noise where the edges can be removed by the suitable edge detector. Thereby the resulting image contains noise only and its variance directly gives the output noise variance. The main drawback of the approach is the assumption of considering difference image to contain only noise is wrong for textured images. In the similar approach given in [18], yields good estimates for large noise cases, but can overestimate the noise in textured images since the texture component can be smoothes out by filtering process. In [10],[12] authors proposed a block based noise estimation algorithm in which variance of the most homogenous block that is detected by minimum block variance is considered to be the output noise variance. The drawback of this approach is that it overestimates the noise level for small noise level and underestimates for large noise level. In [17] pyatikh et al. proposed a PCA based noise estimation algorithm in which a number of similar structure patches (blocks) are detected by discarding blocks of large standard deviation. The method is simple and fast but tends to overestimate the noise for textured images. In [19], this method is extended by using an adaptive threshold of patch variance to select patches. But still it has similar drawbacks as in earlier methods and also it takes large execution time and increases computational load. In [2], a unique method to detect homogenous patch is adopted instead of just thresholding the local variance. A high pass operator is applied on all directions to determine the homogeneity of local block and than a threshold parameter is calculated. But high pass operator is easily affected by noise, leads to poor estimation of noise level in case of textured images containing high level of noise. Local variance based patch selection method gets easily affected by noise and hence suffer from similar drawbacks. In [20],[21] , a unique approach of selecting low rank patches (patches having little or no detail) is given, where a texture strength metric based on the patch gradient covariance matrix is calculated. This method gives remarkable results for estimating noise variance in textured images containing all level of noise added. Some transform based methods have also been presented in [12]-[15]. These methods computes wavelet transform of the input noisy image and assume that the wavelet coefficient at the finest decomposition level correspond only to noise. This often leads to overestimation of noise level for small noise cases and for textured images these coefficients corresponds to image details as well. In [14], some iterative procedure for coefficient thresholding is given. In [15], authors give a procedure to compute residual autocorrelation power (RAP) using range of standard deviation values in order to find the true noise variance. Some statistical approaches are also suggested in literature in which certain image statistics such as median, mode and average of several local estimates are presented in [22]. In [23], the gray value distribution is analyzed. Gray values caused by image structure are considered as outliers and a robust noise level estimator is suggested. In [24], authors proposed a statistical approach to analyze the kurtosis model for the noisy image for best noise variance estimate. Most of the discussed methods are not suitable for estimation of noise variance in textured images. The PCA based estimation algorithm given in [17], [21] works well for plain as well as textured images. In this paper this method is studied well and implemented and later on applied in BayesShrink denoising algorithm for noise reduction f textured images.

3. PCA BASED NOISE VARIANCE ESTIMATION

Let $\overline{y}$ be a noise free image corrupted with additive white Gaussian noise *n* of zero mean and variance σ^2. The noise variance is to be estimated from the input noisy image *y*.

Initially the noisy image is divided in to *N* blocks of size $M_1 \times M_2$. The data model for the block is:

$$y_i = \overline{y_i} + n \quad for\ i = 1 \ldots . N \qquad (1)$$

The PCA based method is based on certain assumptions:

A. The data in the blocks computed from the noise free image is represented by the dimensions smaller than the block size.
B. The presence of constant areas in the image is not required.
C. There is no correlation between signal and noise.

On the basis of the above assumption a brief description of the method as described in [21] is given below.

Since signal and noise are uncorrelated, therefore

$$\sum_y = \sum_{\overline{y}} + \sum_n \qquad (2)$$

Here $\sum_{(y)}$ are the covariance matrices of y, $\overline{y}$ and $\sum_n = \sigma^2 I$

According to assumption A, the minimum Eigen value of the covariance matrix of noise free image is close to zero and hence for such images minimum Eigen value of the covariance matrix of the noisy image is equal to noise variance σ^2 .i.e.

$$\lambda_{min}\sum_y = \lambda_{min}\sum_{\overline{y}} + \sigma^2 \qquad (3)$$

, and hence for images satisfying assumption A

$$\lambda_{min}\sum_y = \sigma^2 \qquad (4)$$

λ_{min} , denotes the minimum Eigen value.

Generally, assumption A is not valid for all types of images especially for textured images or images containing fine detail. Therefore, to make this method applicable for textured images, a subset of image blocks is to be extracted which satisfies assumption A. Such subset of blocks is called low texture blocks. The strategy to extract subset of blocks given in [9]-[11] is to select the blocks with minimum standard deviation or discard the blocks with largest standard deviation. But this criterion overestimates the noise level for textured images. Since it is very difficult to difficult to differentiate between signal and noise for textured images, therefore to extract subset of blocks a texture strength measure to be calculated for each block is proposed by authors in[21]. The texture strength metric is based on the local image gradient matrix and its statistical properties. The texture strength metric is defined as:

$$Z_i = tr\left(C_{y_i}\right) \qquad (5)$$

, where C_{y_i} is a gradient covariance matrix of a block that reflects most of the block information and tr (.) denotes the trace operator. As implied by (5), blocks with small value of texture strength is classified as low texture blocks. Since texture strength depends on the gradient covariance matrix which is easily affected by noise, the effect of noise on it is also investigated. A threshold based on null hypothesis given in [21] and expressed as a function of the confidence level δ and noise σ shown below:

$$\tau = \sigma^2 F^{-1}(\delta, \frac{M^2}{2}, \frac{2}{M^2} tr(D_h{}^T D_h + D_v{}^T D_v)) \qquad (6)$$

Where D_h and D_v are gradient filter matrices, M represents block size. $F^{-1}(\delta, \alpha, \beta)$ is the inverse gamma distribution. The value of δ is mostly set to 1. For the extracted low texture blocks, (4) is applied to estimate noise variance.

4. BAYESSHRINK WAVELET THRESHOLD DENOISING

Let $\overline{y}$ be a noise free image corrupted with additive white Gaussian noise n of zero mean and variance σ^2. The noisy version of the signal is given by:

$$y = \overline{y} + n$$

, where n is an independent and identically distributed (iid) zero mean, white Gaussian noise with standard deviationσ. The goal is to estimate $\overline{y}$ from noisy observation y such that mean squared error (MSE) is minimum. The two-dimensional orthogonal discrete wavelet transforms (DWT) and its inverse is denoted by W and W^{-1} respectively and the noisy and noise free wavelet coefficients are represented by w and $\overline{w}$ respectively. Let x represents the matrix of wavelet coefficients of y having four sub-bands namely *LL*, *LH*, *HL, and HH*. By applying the wavelet thresholding method on each coefficient from the detail sub-band using a hard or soft threshold function, the truncated coefficient matrix B is obtained and denoised image is generated by inverse wavelet transform represented by:

$$\hat{Y} = W^{-1} B \qquad (7)$$

Soft thresholding function is given by:

$$\gamma(x) = sign(x). \max(|x| - T, 0) \qquad (8)$$

It takes the argument and shrinks it towards zero by the threshold *T*. The other popular alternative is hard threshold function given by:

$$\varphi(x) = x, \{if\ |x| > T \qquad (9)$$
$$= 0, \text{otherwise.}$$

Using above functions all the coefficient values less than the threshold in each sub-band is replaced by zero, and the value greater than the threshold is unchanged. In applications, soft thresholding is more preferable over hard thresholding as it gives more visually pleasant images. Finding an optimum threshold is a tedious process. A small threshold value may retain the noisy coefficient while a large value tends to loss of coefficients that carry image details. Many threshold selection processes exists, but in this paper, we mainly focus on BayesShrink thresholding technique.

BayesShrink is a wavelet thresholding technique that uses a Bayesian mathematical framework for image to derive subband dependent thresholds. It provides a threshold that empirically minimizes the Bayesian risk based on the assumption that the image shows properties of generalized distribution (GGD) [14]. The estimated BayesShrink wavelet threshold for each subband is given by:

$$T(\hat{\sigma}) = \frac{\sigma^2}{\sigma_{\overline{w}}} \qquad (10)$$

where σ^2 is the estimated noise variance and $\sigma_{\overline{w}}$ is the standard deviation of noise free subband coefficients. In this paper, the noise variance is estimated using PCA based approach as described in previous section in contrast to the MAD that was used in the original BayesShrink denoising. The estimate of the subband noise free standard deviation is given by:

$$\hat{\sigma}_{\overline{w}} = \sqrt{\max(\hat{\sigma}_w^2 - \hat{\sigma}^2, 0)} \qquad (11)$$

, where $\hat{\sigma}_w^2$ is the variance estimate of the noisy coefficients.

Denoising Algorithm

The denoising algorithm comprises of two parts:

1) Noise variance estimation algorithm
2) BayesShrink denoising algorithm

Noise variance estimation algorithm:

Step 1: Estimate the initial value of the noise variance using all the *N* blocks according to (4).
Step 2: Compute texture metric and threshold according to (5) and (6) respectively.
Step 3: Mark all the blocks whose texture metric is less than or equal to threshold as selected blocks.
Step 4: Estimate the new value of noise variance using the selected blocks using (4) and replace the initial value with this new estimated value.
Step 5: Again go to step 2 and repeat the process until a stable value of noise variance is obtained.

BayesShrink denoising algorithm:

Step 1: Perform five level wavelet decomposition using Haar wavelet on noisy image.

Step 2: Compute BayesShrink threshold by using PCA based noise estimation as described in previous algorithm.

Step 3: Perform BayesShrink thresholding on detail wavelet coefficients according to (8).

Step 4: Perform inverse wavelet transform on truncated wavelet coefficient matrix according to (7) to reconstruct the denoised image.

5. EXPERIMENTAL RESULTS AND DISCUSSION

6. *Noise level estimation experiments*

The PCA based noise level estimator has been tested with eight images containing both textured as well as non-textured images extracted from the image processing literature [20-21]. To test the efficiency of the proposed method, the test images are corrupted with white additive Gaussian noise of standard deviation in the range (10,15,20,25,40] and then the noise level is estimated from the noisy image using different

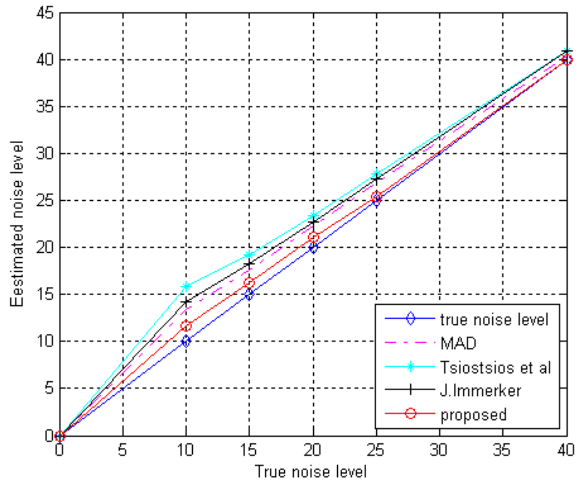


Figure1: The graph showing estimated noise level for noisy baboon image.

algorithms [21], [25-27] including the suggested method referred in this paper. The noise estimation results for all the methods including the proposed one for two test images taken from the test set is displayed in figure1 and figure 2. The graphs in the figure 2 shows that all the four methods estimate the noise level correctly for Lena image but from the figure 1 it can be observed that for baboon image only proposed method gives approximately correct results. The baboon image contain rich textures hence most of the methods overestimate the noise level. The noise level estimation algorithm is implemented in MATLAB version 7.8.0, in Intel® CPU core2duo processor with speed 1.73 GHz, and RAM of size 1.49 GB. The proposed method as discussed in section 3 is compared with other methods and the comparison results are tabulated in Table 1. The estimated noise level can be easily compared with the true noise level from the table and the accuracy of the proposed method is checked. For the data tabulated in Table 1, the performance of the noise estimation can be compared. It can be concluded that methods given in papers [25-27] and the proposed method in [21] gives approximately accurate results for images like Lena, boat where there is less textures.

The methods given in papers [25-27] overestimates the noise level for textured images like baboon, grass and other texture images from the test set. The method in [21] correctly estimates the noise level for all the images included in the test set. For testing the accuracy of the methods for all noise levels, the noise standard deviation [10, 15, 20, and 40] is selected. It can also be verified from Table 1 that the proposed method correctly estimates the noise level for all the values in the noise standard deviation set. Figure 1 shows that the estimated noise level is close to the true noise level for low as well as high noise levels.

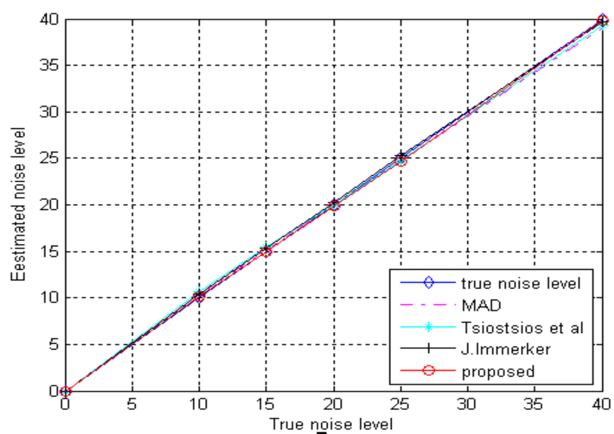


Figure2: The graph showing estimated noise level for noisy Lena image.

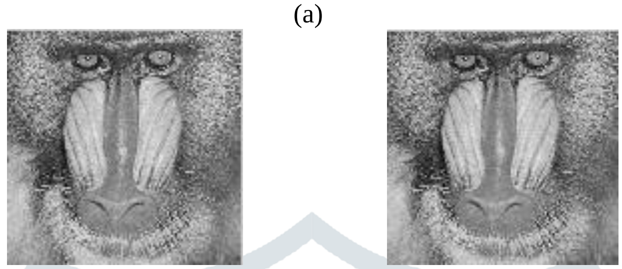
Table. 1: Estimated Noise Level (ENL) for the test images computed for the methods [25-27] and the proposed PCA based method. True Noise Level (TNL) is taken as 10, 20, and 40.

Methods	Estimated Noise Variances						
	Baboon	Lena	Boat	House	Tex1	Tex2	Tex3
TNL=10							
MAD [25]	13.53	10.27	10.77	10.13	11.65	9.39	13.33
Tsiostsios [26]	15.81	10.39	11.12	9.80	****	5.86	46.62
Immerker [27]	14.21	10.40	11.12	10.45	11.83	10.04	13.75
Proposed	11.66	9.79	9.66	10.38	9.99	9.71	10.81
TNL=20							
MAD [25]	22.24	20.05	20.21	19.63	20.59	18.56	21.83
Tsiostsios [26]	23.20	20.08	20.56	18.82	****	11.71	****
Immerker [27]	22.14	20.28	20.51	20.32	20.90	19.23	22.16
Proposed	21.05	19.98	19.86	19.54	20.18	19.48	20.48
TNL=40							
MAD [25]	40.55	38.83	38.59	39.06	39.14	39.32	34.72
Tsiostsios [26]	40.78	39.25	38.64	36.80	52.08	59.04	23.73
Immerker [27]	40.90	39.74	39.23	39.86	39.45	40.10	36.24
Proposed	39.86	38.95	38.57	38.12	38.89	38.96	38.12

Denoising experiments

Finally the noise estimation algorithm is tested in a denoising application. The wavelet based BayesShrink denoising method [14], [15], [28] and anisotropic diffusion denoising algorithm suggested by Tsiostsios [26] which outperforms the algorithms [29] and [30] is utilized for the testing purpose. The BayesShrink denoising algorithm utilizes a wavelet transform. The noise level estimation approach taken in these methods does not work well for images with textures, because textures usually contains high frequencies and effect the finest decomposition level, from which the noise variance is estimated. The noise variance estimation method adopted in [3], [6] assumes that the processed noisy image contain a sufficient amount of homogenous areas. However, this is not always the case, since there are images containing mostly textures. The proposed PCA based noise level estimation algorithm does not restrict to any of such assumptions. The proposed method applied in the denoising application [14] improves its performance both in terms of visual quality and the measured quality metrics Peak signal-to-Noise Ratio (PSNR) and Structural Similarity index (SSIM). The detail of the two quality metrics is given in [31]. The Peak signal-to-Noise Ratio (PSNR) is simple to calculate and has a clear physical meaning, but is not always in accord with human judgment of quality, so the Structural Similarity (SSIM) criterion that is close to human visual system is used as well. For both the two quality measures, a high measure value suggests that the denoised image is closer to the reference noise free image. For all the denoising experiments, the images are taken from the image test set as displayed in Figure 5. The image test set comprises of seven images of size ranging from 256×256 and 512×512 of which baboon, tex1 tex2 and tex3 are mainly textured images. The denoised results of [14] and [26] using the original noise estimation as well as proposed PCA based approach are shown in Figure 3.

(a)



(b) (c)

(d) (e)

Figure 3: (a) Noisy Baboon and boat image (b) BayesShrink denoised[25] Baboon image (c) denoised Baboon image by proposed method (d) BayesShrink denoised[25] Boat image (e) BayesShrink denoised Boat image by proposed method.

The improvement in the quality (PSNR) of the denoised image for the methods can also be visualized by the graphs in figure 4. All the four noise level estimation algorithms are applied to BayesShrink denoising technique and the results are shown in Table 2. Figure 5 shows the test image set used for the denoising experiments. The graph in figure 4 shows the performance of the modified denoising techniques in terms of PSNR that is measured in db.

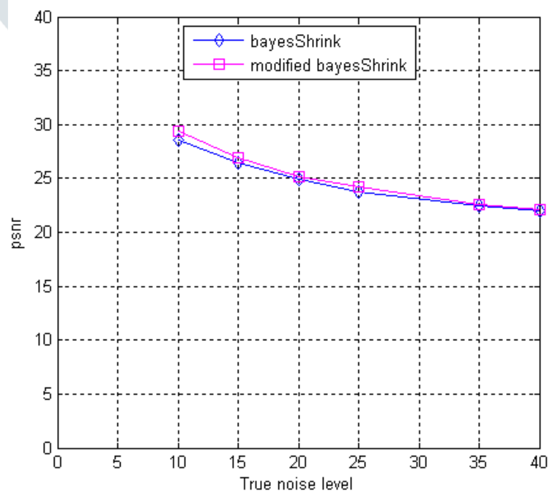


Figure 4: Graph in the figure shows the comparison of the BayesShrink denoising method using proposed noise level estimation approach. Modified BayesShrink implies BayesShrink using PCA based noise variance estimation

Table 2: Comparison of BayesShrink denoising Performance

Methods	Denoised Images PSNR/SSIM						
	Images with True Noise Level (TNL=10)						
	Baboon	Lena	Boat	House	Tex1	Tex2	Tex3
MAD[25]	28.62/.8641	34.07/.8775	31.91/0.8428	33.07/.8418	29.49/.9289	34.66/.8662	28.26/.9647
Tsiostsios[26]	27.51/.8369	34.07/0.8784	31.89/.8437	33.06/.8359	23.38/.7167	30.67/.6059	20.29/.7311
Immerker[27]	28.25/.8573	34.04/.8783	31.90/.8435	32.94/.8411	29.44/.9282	34.62/.8997	28.15/.9637
Proposed	29.46/.8759	34.09/.8682	31.98/.8384	33.07/.8346	29.72/.9330	34.67/.8991	28.97/.9637
TNL=20							
MAD[25]	25.04/.7308	30.89/.8114	28.48/.7370	29.83/.7515	25.57//.8355	30.85/.8458	24.07/.9070
Tsiostsios[26]	24.84/.7208	30.91/.8114	28.42/.7404	29.73/.7368	22.81/.6888	25.36/.3516	19.11/.7090
Immerker[27]	24.97/0.7201	30.86/0.8080	29.43/0.7400	29.74/0.7368	25.51	24.04	24.04
Proposed	25.17/.7383	30.95/.8125	28.51/.7483	29.80/.7365	25.63/.7480	30.40/.8699	24.22/.9110
TNL=40							
MAD[25]	21.98/.5336	28.09/.7463	25.40/.6215	26.80/.6841	22.35/.6940	27.26/.8101	20.31/.7747
Tsiostsios[26]	21.95/.5314	28.01/.7444	25.42/.6254	26.70/.6457	21.27..5941	20.63/.1883	18.75/.6272
Immerker[27]	21.97/.5307	27.98/.7503	25.40/.6250	26.71/.6935	22.34/.6930	27.07/.8384	20.23/.7686
Proposed	22.11/.5479	28.09/.7316	25.42/.6107	26.84/.6450	22.41/.7024	27.34/.7935	20.43/.7857

Baboon Lena Boat House Tex1 Tex2 Tex3

Figure 5: Test Images

7. CONCLUSION

In this paper, the work is mainly focused on estimating noise level close to the true noise variance for noisy images in order to improve the performance of BayesShrink denoising algorithm. Since the denoising performance of this algorithm is not good for textured images, a need arises for suitable noise variance estimator for textured images. The PCA based noise variance estimation method does not require the existence of homogenous areas in the input noisy image and therefore can be applied to textures. This noise level estimation method when applied to BayesShrink denoising gives significant improvement in its denoising performance for all types of images mainly textured images. This improvement in performance is also seen for both low as well as high level of noise. The denoising experiments performed in this paper clearly show the importance of careful selection of noise estimator in a noise reduction application.

Finally it is concluded that the proposed PCA based noise estimator can be successfully utilized not only in image denoising but also in other image processing applications wherever the estimation of noise level in input image is required.

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