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Blind Noise Level Estimation and Blind Denoising Using Principal Component Analysis

***Bheem Prasad Ram*[1], *Sachi Choudhary*[2]**

[1] M. Tech. Scholar, Department of Computer Science and Engineering, School of Engineering & IT, Mats University, Raipur, India
bheemprasadram@gmail.com

[2] Assistant Professor, Department of Computer Science and Engineering, School of Engineering & IT, Mats University, Raipur, India.
Sachi.choudhary1617@gmail.com

Abstract: Noise is important factor in the image processing area .which is effect to visual quality of image and application of image processing like color information, restoration, and enhancement etc. In this paper consider blind noise which has no proper parameter for measure in practically .But this blind noise is already exist in image. In this method estimate to the blind noise from an image using principal component analysis with use parameters as weak texture with low rank texture strength .In this process estimate to the blind noise of an images of each channel (Red ,Green, Blue)noise present in an image. This estimated channel noise is blind noise .which again adding this channel noise in an image by using Bayer pattern. Then Blind noisy image have been denoising by using adaptive non local mean principal component analysis with color demosaicking and finally again estimate to the blind noise level of blind denoising image. Those Estimated noise levels have denoised an image. This is finally possibility of denoised of blind noisy image. The result is better visual quality and smooth sharp image.

Keywords: Blind Noise Level Estimation, Blind Denoising, Principal Component Analysis .Color Demosaicking, Bayer Pattern, Blind noise.

I. INTRODUCTION

In this paper consider blind noise which is present in natural image but not view. This blind noise has no parameter or all ready exist in an image Actually noise is important factor for quality of image and other process of image processing .This Noise is affect to the image therefore noise level estimation and remove are should be important in image processing for improvement the quality of image.

Related researchers are consider noise estimation only which is artifact method filter based approaches, block based approaches and patch based approaches.

Filter based approaches are suppressed to image in high or low frequency so loss to the image information and some properties of image. Therefore estimated noise is not true.

Block based approaches are use local intensity of image .small block are changing intensity of the image in block [5].

Patch based approaches are uses local intensity pixel but non homogeneous patch. Therefore in this method has no stability in estimation of noise level. [3]

This noise level estimation is based on patch based approaches and homogeneous patch selection or random selection of patch according to weak texture and texture strength of image .which give better stability then previous approaches.

In this paper consider simultaneously noise level estimation and blind denoising of an image. This is based on patch based approaches linear patch selection and this denoising is based on non local adaptive with principal component analysis method in this way estimated blind noise are add them by using Bayer pattern in image then Denoised of an image using principal component analysis and color demosaicking which is filed to missing color content of denoising an images. This image is good visual quality, preserving sharp edge and noiseless image

II. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis or simply PCA is statistical concerned with elucidating the Covariance structure of set of variables. In particular it allow us to identify the principal directions in which the varies.

In computational terms the principal components are found by calculating the eigenvectors and eigenvalues of the data covariance matrix. This process is equivalent to finding the axis system in which the co-variance matrix is diagonal. The eigenvector with the largest eigenvalue is the direction of greatest variation the one with the second largest eigenvalue is the (orthogonal) direction with the next highest variation and so on. To see how the computation is done we will give a brief

There are vector variable of simple matrix

$$Z = [z_1\ z_2\ \dots\dots z_m]^T \qquad (2.1)$$

There is m component vector variable

$$Z = \begin{bmatrix} z_1^1 & z_1^2 \dots \dots & z_1^n \\ z_2^1 & z_2^1 \dots \dots & z_2^n \\ z_m^1 & z_m^2 \dots \dots & z_m^n \end{bmatrix} \quad (2.2)$$

The simple matrix of Z, where z_i^j $where$ $j = 1,2 \dots . n$ $z_{i,}$ $i = 1,2 \dots \dots . m$, $z_{i,} = [z_i^1\ z_i^2 \ \dots \dots . z_i^n]$ Is the sample vector of $z_{i,}$ The Mean value $z_{i,}$ can be estimate

Mean value

$$\mu_i = E[z_i] \approx \left(\frac{1}{n}\right) \sum_{j=1}^{n} Z_i(j) \quad (2.3)$$

Thus the mean value vector of Z is

$$\mu_i = E[z_i] = [\mu_1\ \mu_2 \dots . . \mu_m]^T \quad (2.4)$$

Maximum and minimum eigenvalue we can find from covariance matrix sample vector $z_{i,}$

$$C_z = \frac{1}{N} \sum_{i=0}^{N} (z_i - \mu)(z_i - \mu)^T \quad (2.5)$$

Minimum Eigen value = $\lambda_{min} C_z$ (2.6)

Maximum Eigen value $\lambda_{max} C_z$ (2.7)

The inner vector $\bar{z} = z - \mu$ the element of $\bar{z}$ is $\bar{z}_i = z_i - \mu$ the sample vector $\bar{z}_i$ is

$$\bar{Z}_i = Z_i - \mu = [\bar{z}_i^1 \bar{z}_i^2 \dots \dots \bar{z}_i^n] \quad (2.8)$$

Where $\bar{z}_i^j = z_i^j - \mu$.

Accordingly, the inner matrix $\bar{Z}$ of Z can expressed as Follows

$$\bar{Z} = \begin{bmatrix} \bar{Z}_1 \\ \bar{Z}_2 \\ \bar{Z}_m \end{bmatrix} \quad \bar{Z} = \begin{bmatrix} \bar{z}_1^1 & \bar{z}_1^2 \dots \dots & \bar{z}_1^n \\ \bar{z}_2^1 & \bar{z}_2^1 \dots \dots & \bar{z}_2^n \\ \bar{z}_m^1 & \bar{z}_m^2 \dots \dots & \bar{z}_m^n \end{bmatrix} \quad (2.9)$$

Covariance of $\bar{Z}$ Is

$$C_v = E[\bar{Z}\bar{Z}^T] \approx \frac{1}{n}[\bar{Z}\bar{Z}^T] \quad (2.10)$$

Where T is transpose

PCA transformation we can find

The main aim of PCA is find an orthogonal Transformation matrix P Correlation matrix i.e., $\bar{x} = P\bar{z}$ the Covariance matrix of $\bar{x}$ is diagonal. C_v Is Symmetrical, its singular decomposition can be written as.

$$C_v = \Theta \Lambda \Theta^T \quad (2.11)$$

Where $\Theta = [\kappa_1, \kappa_2 \dots \dots . \kappa_m]$ is the mxm orthonormal eigenvector matrix and $\Lambda = \text{diag}\{\lambda_1 \lambda_2 \dots \dots . . \lambda_m\}$ $\lambda_1 \geq \lambda_2 \geq \cdots \dots . . \lambda_m$. The $\kappa_1, \kappa_2 \dots \dots . \kappa_m$ and $\lambda_1 \lambda_2 \dots \dots . . \lambda_m$ are the eigenvectors and eigenvalues of C_v . [7]

$$P = \Theta^T \quad (2.12)$$

$\bar{z}$ Can be decorrelated i.e $\bar{X} = P\bar{Z}$ and

$$\Lambda = \text{E}\,[\bar{\text{X}}\ \bar{\text{X}}^{\text{T}}] \Lambda = \left(\frac{1}{\text{n}}\right) [\bar{\text{X}}\ \bar{\text{X}}^{\text{T}}] \quad (2.13)$$

Transformation matrix as $\text{P}^T = [\kappa_1, \kappa_2 \dots \dots . \kappa_m]$ [7]

The Dimension reduction and Principal component Properties are Described brief in [22][23] .

III. BLIND NOISE LEVEL ESTIMATION

Noise level estimation is important for image processing .In this phase estimate to the blind noise of image as same as Xinhao Liu et al [2].has been proposed for noise level estimation.

In which we Estimate to the blind noise from image by using this framework his proposed by Xinhao Liu et al [2] .In this framework has been some draw back we try to remove this drawback of that framework and improved the efficiencies, accuracy and stability of this framework of noise level estimation. In this main drawback is noise level estimation is overestimate in case of minimum true noise level 1—10 add in image. Because any estimator framework has not give properly 100% work efficiencies therefore cannot say that estimator framework is give 100.2% work efficiency.

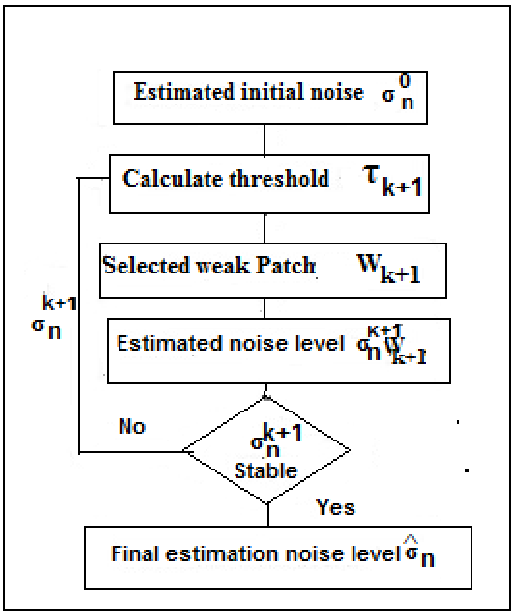

Figure: 1. Framework of Blind Noise Level Estimation [2]

. To drawback for remove use in selection low rank patch with weak texture strength patch is similar structure. Image structure can be measure effectively by the gradient covariance matrices. In this horizontal and vertical derivative operator are directly convert in Toeplitz matrices N^2 x N^2 matrices. And the multiply with the both horizontal and vertical derivative operators are also toeplitz matrix. Then find the result of this framework are no overestimate in any cases when add lower true noise level in image and in case rich texture image. We discussed next section in brief.

IV. BLIND DENOISING OF AN IMAGE

In this section discussed about proposed framework method and blind denoising of blind noisy image .in this following steps:

4.1 Noise level estimate for all channel of the color image.

4.2 Bayer Pattern (add estimated noise in image using Bayer Pattern)

4.3. Denoising of blind noise (using non local mean adaptive principal component analysis with Dimension reduction method)

4.4 Color Demosaicking (It is filled the loss content of primary color of denoise image)

4.1 .Noise level Estimation for all channel of the color image

In this way used framework blind noise level estimation.[2] In which we decomposed image into patch and random selection of the homogeneous patch by using following steps

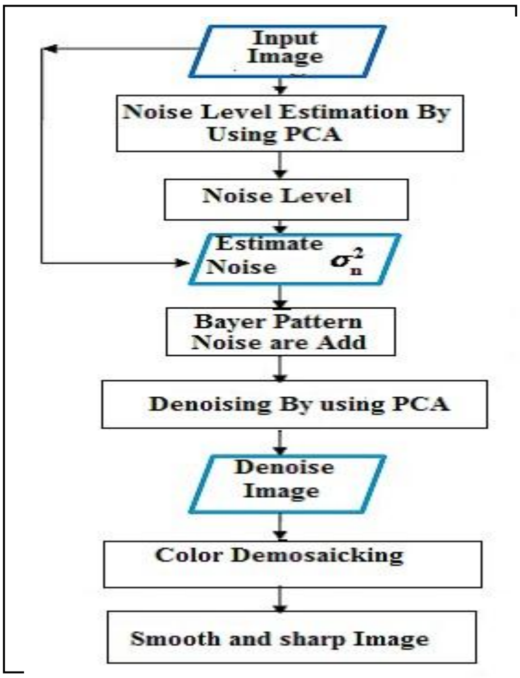

Figure:-2. Proposed Framework of Blind Denoising

4.1.1. Image is Decomposing into patches

Let I is Image, Image size [s1 s2] = size (I)

Patch Size = M1x M2

Where s1 and s2 is number of Columns and number of Rows of the image

Number of Patch N= (s1-M1 +1) * (s2-M2+1)

This Patch can rearranged in vector format with Number of

M =M1xM2 Element in vector of Patch. Z_i Is vector matrix in which contain to the Patch in vector Format. [1]

There is Esq. .no (4.2)

4.1.2. Noise model

$$z_f = X_f + n \tag{4.1}$$

X_f is noise free image and n is assumed noise present in the image

$$z_i = P_g + n_{p_i} \quad i = 1,2,3 \dots \dots n_p \tag{4.2}$$

z_i Is vector of noise patch and P_g is noise free patch, n_{p_i} is the noise patch, n_p is number of patch.

Gradient Covariance matrix

$$G_{z_i} = [D_h(X_f + n) \quad D_v(X_f + n)]$$

$$G_{z_i} = [D_h n \quad D_v n] \tag{4.3}$$

D_h is horizontal and D_v is Vertical gradient derivative which is toeplize matrix.[4]

Gradient covariance matrix $C_{z_f} = [D_h z_i \ D_v z_i]$

Texture strength of patch $f z_f$ become

$$\xi_n = tr\left(C_{z_f}\right) \tag{4.4}$$

That is strength of all noisy patches

$$\xi_i = tr\left(G_{z_f}^T G_{z_f}\right)$$

$$C_z = tr\left(\begin{bmatrix} n^T D_h^T D_h n & n^T D_h^T D_v n \\ n^T D_v^T D_v n & n^T D_v^T D_v n \end{bmatrix}\right)$$

$$= n^T (D_h^T D_h + D_v^T D_v) n \tag{4.5}$$

4.1.3. Threshold Condition for weak texture Selection on Noisy image. [3]

$$\xi(n) \sim gamma\left(\frac{N^2}{2}, \frac{2}{N^2}\sigma_n^2 tra(D_h^T D_h + D_v^T D_v)\right) \tag{4.6}$$

$$\tau = \sigma_n^2 F^{-1}\left(\delta, \frac{N^2}{2}, \frac{2}{N^2} tra\,(D_h^T D_h + D_v^T D_v)\right) \tag{4.7}$$

$F^{-1}(\delta, \alpha, \beta)$ Gamma cumulative distributive function Threshold condition for select the weak textured patches, which define the null Hypothesis.

$$P(0 < \xi(n) < \tau) = \delta \tag{4.8}$$

4.1.4. Noise level estimation for selected Weak texture

Normalized of vector of patches of eq. no (4.2)

$$V(v^T z_i) = V(v^T P_i)$$

Covariance matrix of selected weak texture patch

$$\sum_z = \frac{1}{N}\sum_{i=0}^{N}(z_i - \mu)(z_i - \mu)^T \tag{4.9}$$

$$\lambda_{min} \sum_z = \lambda_{min} \sum_p + \sigma_n^2$$

The minimum eigenvalue of covariance matrix is estimate variance of selected patch

$$\sigma_n^2 = \lambda_{min} \sum_{z'} \tag{4.10}$$

σ_n^2 Is the estimated noise variance .that noise variance are estimated channel wise of image. [2]

σ_r^2 , σ_g^2 , σ_b^2 there is red, green and blue channel noise variance.

4.2. Bayer Pattern

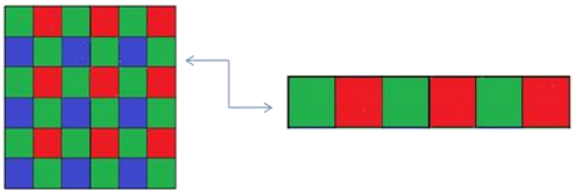

Figure: 3.Bayer Pattern

Green pixel locations are arranged in a quincunx lattice and cover half the array. The red and blue pixel locations are spaced uniformly every two pixels and each cover a quarter of the array. The pattern alternates between “red rows" and “blue rows." In a red row the pattern is R, G, R, and G. and in a blue row it is G, B, G, and B. [24]

In [25], Zhang *et al.* proposed a channel-dependent additive noise model, which is a tradeoff between the signal-dependent noise model and the signal-independent additive noise model

$$\bar{r} = r + \sigma_r^2 \quad \bar{g} = g + \sigma_g^2 \quad \bar{b} = b + \sigma_b^2 \tag{4.2.1}$$

Where σ_r^2 , σ_g^2 and σ_b^2 are the channel noise variance in red, green Blue of image

4.3. Denoising of blind noise

4.3.1. Noise Remove through Principal component analysis

Let Z be the row vector containing all sample dataset of image patch. The patch channel is red green and blue. That vector is containing dataset of training patch and sample is use Bayer pattern for channel. There are the whole data set of z is $Z = [G_1^T\ R_2^T\ B_3^T\ G_4^T]^T$ their $\mu_g, \mu_r, \mu_b, \mu_g$ is mean value of respectively G, R, B, G this average value of all the sample in $G_1\ R_2\ B_3\ G_4$ mean value of training vector is

$$\mu_i = E[z_i] = \left[\mu_{g1} \ \mu_{r2} \ \mu_{3b} \ \mu_{4g}\right]^T \tag{4.3.1.1}$$

The inner mean as $\bar{Z} = Z - \mu$, $\bar{Z} = [G_1^T - \mu_{g1} \ R_2^T - \mu_{r2} \ B_3^T - \mu_{3b} \ G_4^T - \mu_{4g}]^T$ is accordingly to inner dataset of Z.

Noise model

$$\breve{Z} = Z + V \quad (4.3.1.1)$$

Where $V = [V_{g1} \ V_{r2} \ V_{3b} \ V_{4g}]^T$ is the noise variable vector. Noise are add Bayer pattern as channel of image .in which training vector

Inner vector of $\breve{Z}$ is then $\bar{\breve{Z}} = \breve{Z} - \mu$ .Similar to Z we denoted by

$V = [V_{g1}^T \ V_{r2}^T \ V_{b3}^T \ V_{g4}^T]^T$ The available measurement of noiseless dataset X is than $\breve{Z} = Z + V$. we subtract the mean value μ from $\breve{Z}$ is to get the Inner dataset of $\bar{\breve{Z}}$.

$$\bar{\breve{Z}} = \bar{Z} + V \quad (4.3.1.3)$$

The central part of the training patch can be extracted as the denoising patch because boundary samples from the inner part. The whole image can be denoised by moving the denoising patch from top left to bottom right .The way of removing the noise from $\bar{\breve{Z}}$ using PCA Techniques.

Assume that n training sample are available for each element of $\bar{\breve{Z}}$ can be estimated using maximal likelihood estimation MLE.

$$C_{\bar{\breve{z}}} = E[(\bar{z} - E[\bar{z}])(\bar{z} - E[\bar{z}])^T] \quad = \frac{1}{n}[\bar{\breve{Z}}\bar{\breve{Z}}^T] \quad (4.3.1.4)$$

$$= \frac{1}{n}\bar{Z}\bar{Z}^T + \bar{Z}V^T + V\bar{Z}^T + VV^T \quad (4.3.1.5)$$

Since the $\bar{Z}$ and V are uncorrelated, items $\bar{Z}V^T$ and will be nearly zero matrix .which reduces the following

$$C_{\bar{\breve{z}}} = C_{\bar{z}} + C_V = \frac{1}{n}(\bar{Z}\bar{Z}^T + VV^T) \quad (4.3.1.6)$$

$C_V = \frac{1}{n}VV^T \quad C_{\bar{z}} = \frac{1}{n}[\bar{Z}\bar{Z}^T]$ Covariance matrices of $\bar{Z}$ and V respectively.

The noise vector $V = [v_{g1} v_{r2} v_{b3} v_{g4}]$

$$C_V = E[\bar{V}\,\bar{V}^T] \quad (4.3.1.7)$$

$= diag\{\sigma_g^2, \sigma_r^2, \sigma_b^2, \sigma_g^2\}$ Where $\sigma_g \sigma_r$ σ_b are standard deviations of channel dependent noise variance.

The covariance of $\bar{Z}$ can be calculated as $C_{\bar{z}} = C_{\bar{\breve{z}}} - C_V$.

This negative value of $C_{\bar{z}}$ in the diagonal positions. This is replacing the negative value with the zero or small positive number.

We known PCA transform of $\bar{Z}$ there are discussed in above section II eq. No (2.12)

Decomposition of $C_{\bar{z}}$ is

$$C_{\bar{z}} = \Theta \Lambda_{\bar{z}} \Theta_{\bar{z}}^T \quad (4.3.1.8)$$

Where $\Theta_{\bar{z}} = [\kappa_1, \kappa_2 \ldots\ldots\kappa_m]$ is the mxm orthonormal eigenvector matrix where m is patch size and $\Lambda_{\bar{z}} = \mathrm{diag}\{\lambda_1 \lambda_2 \ldots\ldots\lambda_m\}$ $\lambda_1 \geq \lambda_2 \geq \cdots \ldots\lambda_m$.The $\kappa_1, \kappa_2 \ldots\ldots\kappa_m$ and $\lambda_1\lambda_2 \ldots\ldots\lambda_m$ is the eigenvectors and eigenvalues of C_v .there is discussed in above equations. (2.11) and (2.12)

Orthogonal transformation matrix for $\bar{Z}$ is than

$$P_{\bar{z}} = C_{\bar{z}}^T \quad (4.3.1.9)$$

Applying $P_{\bar{z}}$ to the noisy dataset $\bar{\breve{Z}}$ resulting in the following

$$\bar{\breve{X}} = P_{\bar{z}}\bar{\breve{Z}} = P_{\bar{z}}(\bar{Z} + V) = P_{\bar{z}}\bar{Z} + P_{\bar{z}}V$$

$$= \bar{X} + V_X \quad (4.3.1.10)$$

Where $\bar{X} = P_{\bar{z}}\bar{Z}$ Is the decor related dataset for signal and $V_X = P_{\bar{z}}V$ is the Trans formed noise dataset for noise. Since $\bar{X}$ and noise V_X are uncorrelated, the covariance matrix of $\bar{\breve{X}}$ is

$$C_{\bar{\breve{X}}} = C_{\bar{X}} + C_{V_X} = \frac{1}{n}\bar{\breve{X}}\bar{\breve{X}}^T \quad (4.3.1.11)$$

Where $C_{\bar{X}} = \Lambda\Lambda_{\bar{z}} \approx \frac{1}{n}\bar{X}\bar{X}^T$

$$C_{V_X} = P_{\bar{z}}C_V P_{\bar{z}}^T \approx \frac{1}{n}V_X V_X^T \quad (4.3.1.12)$$

Are the covariance matrices of $\bar{X}$ and V_X respectively.

Resetting the last several rows (the least important component s) of $\bar{\breve{X}}$ will be removing the noiseV_X. This operation is actually based on optimal dimension reduction property of PCA. [7]

We denoted by $\bar{\breve{X}}^d$ the dimension Reduced (by last several rows as zeros) dataset of $\bar{\breve{X}}$ and $\bar{\breve{X}}^d$ Can be written as $\bar{\breve{X}}^d = \bar{X}^d + V_X^d$,$\bar{X}^d$ V_X^d Represents, respectively, the dimension reduced dataset of $\bar{X}$ and V_X.

Similarly the corresponding co-variance matrix, denoted as $C_{\bar{\breve{X}}}^d$ $C_{\bar{X}}^d$ and$C_{V_X}^d$ are related as

$$C_{\bar{\breve{X}}}^d = C_{\bar{X}}^d + C_{V_X}^d \quad (4.3.1.12)$$

We further improve the efficiency of denoise and missing content are filed by color demosaicking .there are discussed below

4.3.2. Color Demosaicking

In order to reconstruct a full color image the missing color samples need to be interpolated by a process called color demosaicking. The quality of reconstructed color images depends on the image contents and the employed demosaicking algorithms. In all color demosaicking techniques gradient analysis plays a central role in reconstructing sharp edges.

In These observations provide a rationale for estimating the color difference signals by linear minimum mean square-error estimation (LMMSE) method, which yields a good approximation to the optimal estimation in mean square-error sense. The LMMSE estimates are obtained in both horizontal and vertical directions, and then fused optimally to remove the demosaicking noise. Finally, the full resolution three color channels are reconstructed from the LMMSE filtered difference signals.

These adaptive demosaicking is the selection of the direction of color interpolation. , we make two separate estimates of a missing primary color sample in both 8 horizontal and vertical directions.

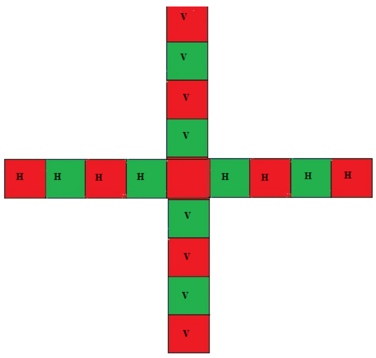

Figure 4: Color Sampling (Horizontal and vertical Direction)

The demosaicking of input data A The input mosaic image, Bayer Pattern as follows G, R, G, and R. And B, G, B, G.

If A is a full color image, it will be down sampled according to Bayer pattern. [21]

The noise in dimension reduction dataset $\bar{X}^d$ can be further suppressed by using linear minimum mean squared error estimation LMMSE .the LMMSE of $\bar{X}^d$ i.e the i th row of $\bar{X}^d$ is obtained as

$$\hat{\bar{X}}_i^d = c_i . \bar{X}_i^d \qquad (4.3.2.1)$$

Where $c_i = C_{\bar{X}}^d(i,i) + C_{V_X}^d(i,i)$

Applying (4.3..1) to each non zero row of $\bar{X}^d$ yields the full denoised dataset $\hat{\bar{X}}^d$ now the denoising result of the original dataset $\bar{\bar{Z}}$ the estimation of unknown noiseless dataset $\bar{Z}$ can be obtain as follows:

$$\bar{\bar{Z}} = P_Z^{-1} . \hat{\bar{X}}^d \qquad (4.3.2.2)$$

Repeating and Rearrange the $\bar{\bar{Z}}$ result in the Denoised image patch.

V. RESULT DISCUSSION

Image quality assessment like MSE, Standard Deviation and PSNR are best measurement parameters. Which define how many noise are present in image and quality of image are define by the MSE and PSNR. There minimum standard deviation is measure quality of estimator and high PSNR and Low MSE is measure best Denoise.

We discussed two type results testing of our proposed method:

5.1 Additive Gaussian noise testing for mapping noise level estimator efficiency, accuracy and stability of result.

5.2 Blind Noise level Estimation and Blind Denoise result

5.1 additive Gaussian noise testing for mapping noise level estimator efficiency, accuracy and stability of result.

We discussed about proposed result .that is additive Gaussian noise testing results of noise level estimator. Given below table 1 to 4. The table 1 is show True noise Vs Estimate noise level (Before Denoising) and Estimated noise Level after Demoising.

This is defining the estimator efficiency, stability, and accuracy of estimation Noise level. The table 2 is show True noise Vs Peak Signal to Noise Ratio (PSNR) is before denoising and (NPSNR) is After Denoising. The Table 3. Is showing True Noise Vs Mean Squire Error, where (MSE) is before Denoising and (NMSE) is After Denoising. And Table 4. Is show true Noise Vs signal to Noise ratio, where (SNR) is before Denoising and (NSNR) after Denoising.

Figure: 5 Hills Image (Testing Image)[2]

True Noise	ENL			NENLE		
	Red	Green	Blue	Red	Green	Blue
5	4.9326	4.928	4.9147	0.1808	0.2301	0.3067
10	9.7494	9.8224	9.8126	0.1716	0.217	0.2876
20	19.6858	19.6782	19.6528	0.1511	0.1958	0.259
40	39.1986	39.364	39.2352	0.154	0.1702	0.2217

Figure .1.Table of Noise Level Estimation Before and After Denoise of Image

True Noise	PSNR			NPSNR		
	Red	Green	Blue	Red	Green	Blue
5	34.14523	34.1428	34.1767	55.5600	54.5108	53.2639
10	28.16434	28.13274	28.12126	55.7860	54.7659	53.5432
20	22.11319	22.12020	22.11253	56.3378	55.2125	53.9974
40	16.0666	16.10095	16.1113	56.2568	55.8201	54.6736

Figure .2.Table of Peak Signal to Noise Ratio Before and After Denoise of Image

True Noise	MSE			NMSE		
	Red	Green	Blue	Red	Green	Blue
5	25.035	25.04952	24.85452	0.18075	0.23014	0.30668
10	99.230	99.9553	100.2197	0.17158	0.21701	0.28758
20	399.724	399.080	399.7855	0.15111	0.19580	0.25902
40	1608.46	1595.824	1592.005	0.15395	0.17024	0.22167

Figure .3.Table Mean Square Error Before and after Denoise of Image

True Noise	SNR			NSNR		
	Red	Green	Blue	Red	Green	Blue
5	34.138	34.130	34.179	55.486	54.331	53.115
10	28.154	28.129	28.111	55.756	54.577	53.377
20	22.125	22.141	22.111	56.296	55.011	53.744
40	16.084	16.103	16.104	56.252	55.674	54.421

Figure .4.Table Signal to Noise Ratio Before and after Denoise of Image

In the below show graph are draw accordance to above discussed table .in this figure 3 are Noise level estimation are True Vs Estimated noise level in Red Channel of image, Figure 4 are Noise level estimation and Denoise of image for Green Channel and Figure 5 are Noise level estimation and Denoise of image for Blue Channel .and also figure 6, 7 are Graph for PSNR, MSE and SNR of image before and after Denoise, this graph is practical approach for Blind Noise estimation and Denoise of a natural and any user input image without add noise. That graph is show performance of our proposed method.

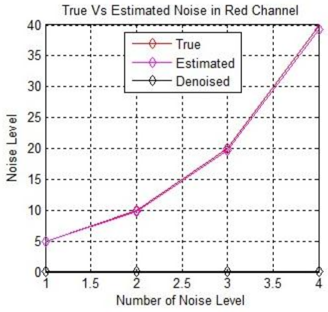

Figure 6: Noise level Estimation before and after Denoise of Red Channel of Image

Figure 6 .In figures Red color is True Noise, Pink Color is Estimated Noise Level before Denoising and black color line is show Denoise after Noise level

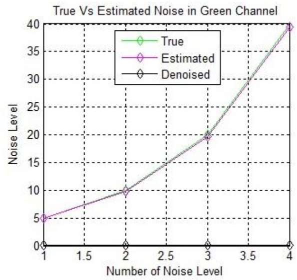

Figure 7: Noise Level Before and after Denoise of green Channel of Image

Figure 7 .In figures Green color is True Noise, Pink Color is Estimated Noise Level before Denoising and black color line is show Denoise after Noise level.

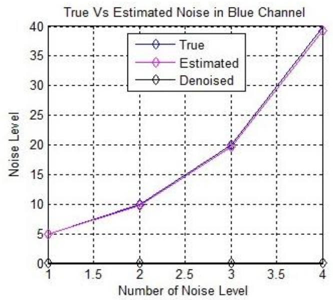

Figure .8. Noise Level Before and after Denoise of Blue channel of Image

Figure 8 .In figures Blue color is True Noise, Pink Color is Estimated Noise Level before Denoising and black color line is show Denoise after Noise level

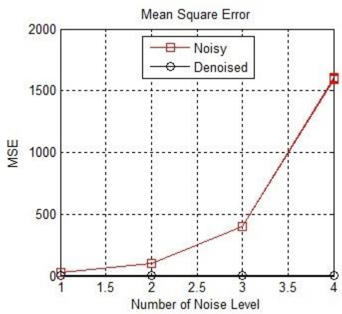

Figure 9 .In figures Red color is show before Denoise image Mean Squire Error, Black Color is after Denoising Mean Squire Error of proposed method.

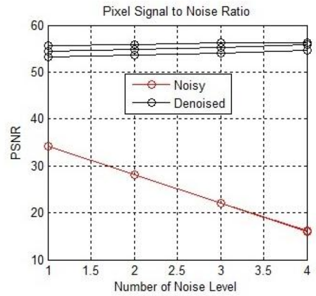

Figure .10. Peak Signal to Noise Ratio before and after Denoise of Image

Figure 10 .In figures Red color is show before Denoise image Peak Signal to Noise Ratio, Black Color is after Denoising New Peak signal to noise Ratio of proposed method

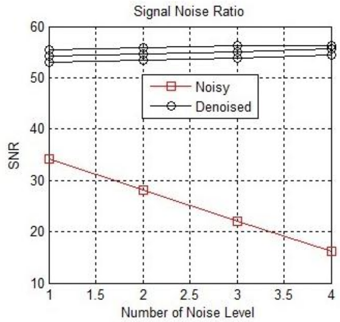

Figure .11.Table Signal to Noise Ratio Before and after Denoise of Image

Figure 11 .In figures Red color is show before Denoise image Signal to noise Ratio, Black Color is after Denoising New Signal to noise Ratio of proposed method

5.3 Blind Noise level Estimation and Blind Denoise result Testing image which Shown in figure (5) hill images.

S.no.	Red	Green	Blue
Estimated Blind Noise	0.0386	0.0386	0.0392
Denoising then Estimated Noise	0.008315	0.008773	0.009213
PSNR	29.9117	30.9103	30.0176
SNR	28.9567	29.9553	29.0626

Figure .5 Tables is Describe result of Blind Denoising of an image When Denoise. First row show Noise level Estimation channel wise befor Denoise and third row is show

Estimated Noise level channel wise when blind Denoised. Fourth and fifth row show performance of Denoising peak signal to noise ratio and signal to noise ratio. The higher value of PSNR and SNR is described the good quality of Blind Denoise.

VI. CONCLUSION

In this paper proposed simultaneously blind noise level estimation and blind denoising without prior knowledge of noise level of image.Becouse blind noise has no parameter for measurement. This noise is exist already in image. This framwork estimate blind noise present in image. The noise level estimation and blind denoise both are based on principal component analysis method. This noise level is estimate by parameter weak texture patch and low rank texture strength. The noises are calculate by minimum eigenvalue of covariance matrix of weak texture or selected patch. Estimated noise is added Bayer pattern in image .then Denoising to the image using principal component analysis by diamention reduction propertiesThe color demosaicking is use for filed the missing content of denoising image and further suppress to the noise of image. The output image is better visual quality and smooth sharp image.

REFERENCES

[1] S. Pyatykh, J. Hesser, and L. Zheng, “Image noise level estimation by principal component analysis,” IEEE Trans. Image Process., vol. 22, no. 2, pp. 687–99, Feb. 2013

[2] Xinhao Liu, Masayuki Tanaka, and Masatoshi Okutomi,“Noise level estimation using weak textured patches of asingle noisy image,” in IEEE International Conference on Image Processing, 2012, pp. 665–668

[3] Xinhao Liu, Masayuki Tanaka, and Masatoshi Okutomi “Single-Image Noise Level Estimation for Blind Denoising”,IEEE trans. Image Processing, VOL. 22, No. 12, October 2013

[4] X. Zhu and P. Milanfar, “Automatic parameter selection for denoising algorithms using a no-reference measure of image content,” IEEE Trans. Image Process., vol. 19, no. 12, pp. 3116–32, Dec. 2010..

[5] D.H .Shin, R-H.Park.S.Yang and J-H.Jung “Block-based noise estimation using adaptive Gaussian filtering” IEEE Trans, Consumer Election vole 51 no1 –pp,218-226 Feb 2005

[6] Wavelet-Based Despeckling of Synthetic Aperture Radar Images Using Adaptive and Mean Filters

[7] Lei Zhang, R. Lukac, X. Wu and D. Zhang, “PCA-based Spatial Adaptive Denoising of CFA Images for Single-Sensor Digital Cameras,” IEEE Trans. on Image Processing, 2009.

[8] Xiaogang Chen1,3,4, Sing Bing Kang2, Jie Yang1,3, and Jingyi Yu4 “Fast Patch-based Denoising Using Approximated Patch Geodesic Paths”

[9] Phillip K Poon, Wei-Ren Ng, Varun Sridharan ”Image Denoising with Singular Value Decompositon and Principal Component Analysis” December 8, 2009

[10] I Romero IMEC, Eindhoven, the Netherlands “PCA-based Noise Reduction in Ambulatory ECGs”, pp-677-680 ISSN-0276-654,26-29 Sept. 2010

[11] L. Zhang and X. Wu, “Color demosaicking via directional linear minimum mean square-error estimation,” IEEE Trans. on Image Processing, vol. 14, pp. 2167-2178, Dec. 2005

[12] Zhang -Wu "Directional LMMSE Image Demosaicking" image processing online (2011)

[13] Lei Zhang, Rastislav Lukac, Xiaolin Wu and David Zhang,"PCA Based Spatially Adaptive Denoising of CFA images for Single- Sensor Digital Cameras" IEEE Transactions on Image Procession,VOL. 18, NO. 4, APRIL 2009.

[14] D. D. Muresan and T.W. Parks, “Adaptive principal components and image denoising,” in IEEE ICIP, 2003, vol. 1, pp. 101–104.

[15] Zhang, W. Dong, D. Zhang, and G. Shi. Two-stage image denoising by principal component analysis with local pixel grouping. Pattern Recogn., 43(4):1531–1549, 2010.

[16] Buades, B. Coll, and J.-M. Morel, “A non-local algorithm for image denoising,” in IEEE CVPR, 2005, pp. 60–65.

[17] D. Zoran and Y. Weiss, “Scale invariance and noise in natural images,” in Computer Vision, 2009 IEEE 12th International Conference on. IEEE, 2009, pp. 2209–2216

[18] Tasdizen, “Principal components for non-local means image denoising,” in Image Processing, 2008. ICIP 2008. 15th IEEE International Conference on. IEEE, 2008, pp. 1728–1731.

[19] Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Bm3d image denoising with shape-adaptive principal component analysis,” in Proc. workshop on signal processing with adaptive sparse structured representations (SPARS09), vol. 49. Citeseer, 2009.m

[20] Charles-Alban Deledalle,Joseph Salmon and Arnak Dalalyan.”Image Denoising with Patch Based PCA: Local Versus global”Proceeding of the British Machine Vision Conference,Pages 25.1-25.10.BMVA Press,Septembr 2011.

[21] L.Zhang and X. Wu, “Color demosaicking via directional Linear minimum mean square-error estimation,” IEEE Trans. Image Process. vol.14, no. 12, pp. 2167–2178, Dec. 2005.

[22] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd ed.Englewood Cliffs, NJ: Prentice-Hall, 1999.

[23] K. Fukunaga, Introduction to Statistical Pattern Recognition, 2nd ed.New York: Academic, 1991.

[24] Zhang -Wu "Directional LMMSE Image Demosaicking" image processing online (2011).

[25] L. Zhang, X. Wu, and D. Zhang, “Color reproduction from noisy CFA data of single sensor digital cameras,” IEEE Trans. Image Process., vol. 16, no. 9, pp. 2184–2197, Sep. 2007.

Bheem Prasad Ram[1] received the B.E degrees in Information Technology from Kirodimal Institute of Technology Raigarh India 2012 and currently pursuing Mtech in Computer Science and Engineering, Area of interest Image Processing.
Email:-bheemprasadram@gmail.com

Ms. Sachi Choudhary[2]
1. Mtech in Computer Science and Engineering. Area of interest distributed system, Image processing, Computer Network cryptography and network security.
2. International journal 2 conference. .
Email:-sachi.choudhary1617@gmail.com