A Novel Approach for Image Noise Estimation and its Removal

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***Abstract*—**Noise is caused by the digital sensor attempting to record tiny amounts of light. Basically the camera is trying to record what is too dark to record clearly and, as a result, stray electrical signals wind up on the finished picture as flecks, or noise. The faster ISO you set on your digital camera, the more noise increases as it picks up smaller and smaller electrical signals This noise will distort and affect the quality of the image. There are different types of noises and depending upon the image the noise will be varied. The most common types of noises are Gaussian Noise, Salt and pepper noise and Speckle noise. Enhancement of a noisy image is necessary task in Image Processing. Here we are aiming to estimate the type of noise present in an image with the help of the parameters such as PSNR, MSE and then in order to remove the noise, we use adaptive subband thresholding technique.

Keywords—*Digital Image,Image Noise,Gaussian Noise,Salt and Pepper Noise,Speckle Noise,Noise Estimation,PSNR,MSE*

I. INTRODUCTION

A binary representation of visual information such as drawings, pictures, logos, graphs or individual video frames is termed as an 'Image', 'Digital Image' or a 'Still Image'. Images can be stored on any storage device electronically. Images can be two dimensional or three dimensional[1]. A 'Still Image' is a single static image. A 'Moving Image' is basically a movie or film. A 'Still Frame' is one that is derived one frame of a moving image.The image generally is corrupted by noises. The quality of the image is affected and distorted by this noise. There are different types of noises present. The most common types of noises are Gaussian Noise, Salt and pepper noise and Speckle noise. Enhancement of a noisy image is a much needed work to be done in Image Processing[1]. A common procedure in digital image processing aiming to remove the noise which may corrupt an image during its acquisition or transmission while maintaining its quality is termed as 'Image Denoising'. Images with poor quality are not useful for further application because of uneven illumination, image blurring, and low contrast[2]. Blur and Noise are the two main limitations when it comes to image accuracy.

As digital images have a finite number of samples blur is an intrinsic factor in image acquisition systems. The next important disturbance found in an image is noise. Random variation of brightness or color information in images is termed as 'Image Noise'[2]. Image noise obscures the desired information by being an undesirable by-product. Noise often means 'Unwanted Signal'. Image noise ranges from small disturbances on a digital photograph to optical and radioastronomical images that are full of noise[3]

As noise in images during image processing deprecates its quality, to improve the quality many algorithms were proposed and suggested which made a positive impact and performed an optimal functioning[4]. Most of the algorithms suggest for changing the neighbouring pixel values through filters for which different types of filters were available which remove the noise from images. But most of these algorithms whether determine the actual differences in pixel values comprises of noise or detail of the real photograph and average out the former by attempting to preserve the latter[4]. Noise in the Images has random variation that may be in terms of their information, colour or brightness. Estimation of noise in single image is quite typical task and seems to be next to impossible; in that it is hard to find the cause of variation in image it may be due to brightness, texture or colour due to noise or from itself.

Denoising algorithms usually don't differentiate between small details of an image and noise present in an image, so they remove them[5]. New distortions are created by them in many cases and the researchers are so much used to them as to have created a taxonomy of denoising artifacts. The goal of image denoising methods used here is to recover the original image from a noisy environment retaining the minute details of the image[4].

The equation of an corrupted with noise is given by:

$$v(i) = u(i) + n(i) \qquad (1)$$

where $v(i)$ is the observed value

$u(i)$ is the "true" value and

$n(i)$ is the noise perturbation at a pixel i

II. TYPES OF IMAGES

The different types of images that are considered in image processing are as follows:

1) BINARY IMAGE

In this image, every pixel is either black or white. Here only one bit per pixel is needed as there are only two possible values for each pixel. These kind of images are very efficient for storage. Images like fingerprints, content(printed or handwritten), or structural arrangements are suitable for binary representation[5].

2) GRAYSCALE IMAGE

Each pixel is a shade of gray, normally from 0 (black) to 255 (white). This range means that every pixel can be represented by eight bits, or exactly one byte. For handling AN image file this range is inevitable. For different grayscale images, the range of pixels are generally power of 2. These kind of images are suitable in images of printed works, medicine(Xrays) and also for recognizing most of the natural objects or scenes 256 different grey levels are sufficient[5].

3) INDEXED IMAGE

An indexed image consists of an array and a color map matrix. The pixel values in the array are direct indices into a color map. By convention, this documentation uses the variable name X to refer to the array and map to refer to the color map[5].

4) TRUE COLOR OR RGB IMAGE

In these type of images, Each pixel has a particular color; that color is described by the amount of red, green and blue in it. If each of these components has a range 0–255, then the image adds up to estimation of 255^3=16,777,216 feasible colors. For any image these colors are sufficient. RGB images are likewise called 24-bit images because total number of required bits for each pixel is 24. Such an image is a "stack" of three matrices; representing the red, green and blue values for each pixel. This means that for every pixel there correspond 3 values[5].

III. TYPES OF NOISES

There are three types of noises which we are considering here. They are given as below:

a)GAUSSIAN NOISE

A statistical noise which has a probability density function (pdf) equal to the probability density function (pdf) of a normal distribution /distribution is known as 'Gaussian Noise'[5][6].

PDF 'p' of Gaussian random variable is given by

$$P_G\,(z) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{\frac{-(z-\mu)^2}{2\sigma^2}} \qquad (2)$$

'z' represents the grey level, μ the mean value and σ the standard deviation

b)SALT AND PEPPER NOISE

Salt and pepper noise is also known as 'Impulse Noise'. The sharp and sudden disturbances in the image signal causes salt and pepper noise. It is usually the black and white pixels seen in the image. An image containing salt and pepper noise will have dark pixels in bright regions and bright pixels in dark regions[5][6].

PDF of salt and pepper noise is as given below

$$p(g) = \begin{cases} p_a \; if \; g = a \\ p_b \; if \; g = b \\ 0 \; otherwise \end{cases} \qquad (3)$$

c)SPECKLE NOISE

Speckle noise is a 'Granular Noise' that exists in and degrades the quality of Active Radar, Synthetic Aperture Radar(SAR), Medical Ultrasound and Optical Coherence homography images. Speckle noise is caused primarily by the interference of the returning wave at the transducer aperture. The pattern of constructive and destructive interference shown as bright and dark dots in the image results in causing the speckle noise[5][6].

PDF of speckle noise with '2 α' variance and 'g' gray level is given by

$$f(g) = \left\{\frac{g^{\alpha-1}}{(\alpha-1)!\,\alpha^{\alpha}}\right\} e^{\frac{-g}{\alpha}} \qquad (4)$$

IV. RELATED WORK

In paper[1] Traditional noise estimation methods are designed for the homogeneous white Gaussian noise (WGN), which can be represented by the noise variance (the point model). In reality there are many noise sources in real imaging process, such as dark-current noise, shot noise, fixed-pattern noise etc, which cannot be modeled by WGN. In paper[2] Poisson-Gaussian model is used to model signal dependent noise. The noise level depends on the image intensity. This model is suitable for raw images or linear imaging systems. It is unsuitable for JPEG images, which are the most popular image format used by most consumers and vision researchers. In paper[3] the proposed method describes a new method for suppression of noise in image by fusing the wavelet denoising technique with optimized thresholding function to which a multiplying factor (α) is included to make the threshold value dependent on decomposition level. The proposed threshold estimation method is based on the analysis of statistical parameters like standard deviation, variance of the sub band coefficients.Paper[4] tells that there are three type of noises that can be introduced in image noise estimation and noise removal on various digital images. Before analysis or using image to ensure the quality of image in image processing noise estimation and removal are very important step. Due to low contrast and high noise in an image most algorithms have not yet attained a desirable level of applicability. This paper deals with image de-noising by using the PCA (principal component analysis), Median filter and wavelet analysis. The noise content present in the image was not completely removed. This won't work for images corrupted with higher noise density.The estimation and removal of noise is not so robust. Paper[5] in recent years, many new enhancement methods for noise reduction have been proposed. For estimation and removal of noise from the image some basic algorithm were proposed such as Contour based Segmentation and Functioning of PCA for Estimation and Removal of Noise in which Estimation of noise in image through PCA and Removal of noise from Image through PCA is done. But Contour segmentation algorithm is used for segmentation and not for noise removal.

V. PROPOSED SYSTEM

In our work an efficient approach for estimation and removal of noise from an image has been proposed. This algorithm fulfills the number of objectives related to noise estimation and its removal such as Noise should be mostly removed from the affected regions and there should be no loss in detail of texture of the image.At first to train the system, the noise content is added to the original input image. The commonly used noises such as Gaussian noise, Salt and Pepper Noise and speckle noise is added to the input image which forms the noisy image. The Noises are added in certain amounts(10%). Now we measure the PSNR and MSE parameters.Then increase the content of noise to 20% in the image . Now measure the PSNR and MSE parameters. We need to repeat it for all three types of noises till 50%.

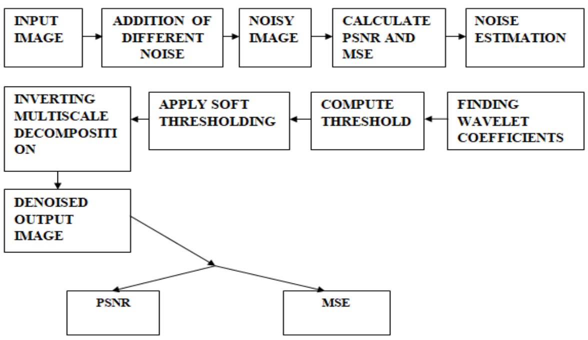


Fig 1.Image Noise Estimation and Denoising

Now we test the system for that we take a new image that is corrupted by unknown noise as input and measure the same parameters of the corrupted image. Noting down the parameters measured of new corrupted image, we compare them with the already PSNR and MSE parameters of the original image and calculate the image absolute difference between the MSE's of all the noise added images and the new image that is taken. The image that gives the minimum absolute difference is considered and the noise that is present in that image is estimated to be present in the new corrupted image.

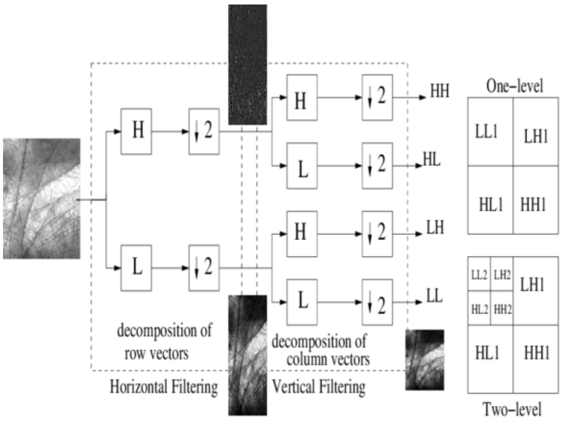
Next step is to denoise that image if it is corrupted by Gaussian noise. For that the window size has to be set. The signal variance of a coefficent will be estimated using neighboring coefficients in a rectangular region with this window size. Stages that will be used for the wavelet transform has to be calculated . The noisy image will be extended using symmetric extension in order to reduce the boundary problem with a function symextend.m. Calculate the forward wavelet transform. Estimate the noise variance. The noise variance will be calculated using the robust median estimator. Process each subband seperately. We will process each subband in a loop since our implementation stores the wavelet coefficients in a cell array. First the coefficent and the corresponding parent matrices are prepared for each subband, and the parent matrix is expanded using the function expand.m in order to make the matrix size the same as the coefficient matrix. Estimate the signal variance and the threshold value : The signal variance for each coefficent is estimated using the window size and the threshold value for each coefficient will be calculated and stored in a matrix with the same size as the coefficent matrix.

Estimate the coefficients. The coefficients will be estimated using the noisy coefficient, its parent, and the estimated threshold value with the Matlab function bishrink.m. Calculate the inverse wavelet transform. Extract the image. The neccessary part of the final image is extracted in order to reverse the symmetric extension operation.

VI. DISCRETE WAVELET TRANSFORM

DWT is the multi-resolution description of an image the decoding can be processed sequentially from a low resolution to the higher resolution. The DWT splits the image into high and low frequency parts. The high frequency part contains information about the edge components, while the low frequency part is split again into high and low frequency parts.

In two dimensional applications, for each level of decomposition, we first perform the DWT in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1, and HH1.



The DWT is applied to the image. The Approximation, Horizontal, Vertical and Diagonal Coefficients are obtained for the image. The LL coefficients are considered for further process. It is decomposed to 1 or 2 levels. The Mean, Standard Deviation, Variance are calculated for the decomposed DWT image. These feature values are considered for next level.

Considering the advantages and limitations of the statistical model a new model is proposed based on the wavelet coefficients. Wavelet coefficients with large magnitudes are representatives of edges or some textures, while those with small magnitude are associated with smooth regions such as the background. In this smooth region the signal variance for every sub-band are estimated by a ML estimator. This method presents effective results but their spatial adaptivity is not well suited near object edges where the variance field is not smoothly varied. Noise variance is found using robust median estimator. The equation is as given below:

$$\sigma_V^2 = \left(\frac{median\left|y(V)\right|}{0.6745} \right)^2 \tag{3}$$

VII. RESULTS

Given below are the images showing various results of training the system using our proposed framework:

Fig 2. Images after adding 10% of different noises

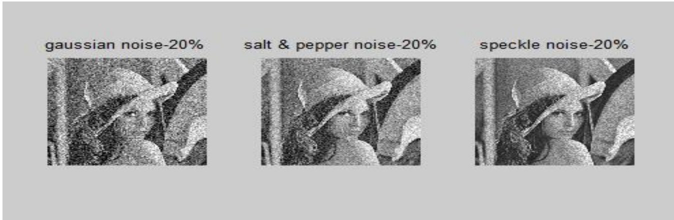


Fig 3. Images after adding 20% of different noises

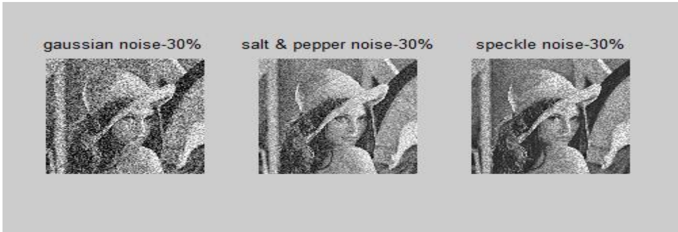


Fig 4. Images after adding 30% of different noises

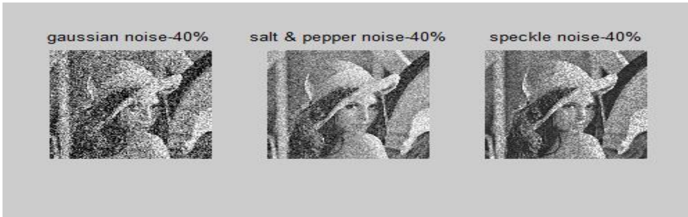


Fig 5. Images after adding 40% of different noises

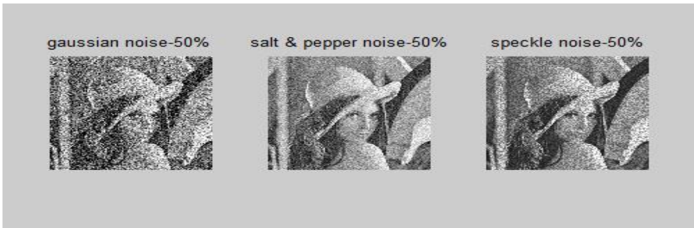
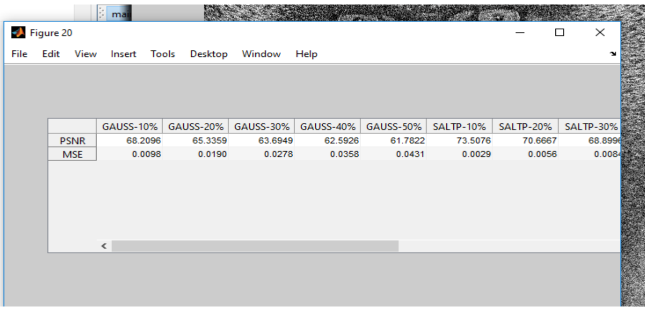


Fig 6. Images after adding 50% of different noises

Now we calculate PSNR and MSE of all the images. The result is as shown below:



	GAUSS-10%	GAUSS-20%	GAUSS-30%	GAUSS-40%	GAUSS-50%	SALTP-10%	SALTP-20%	SALTP-30%
PSNR	68.2096	65.3359	63.6949	62.5926	61.7822	73.5076	70.6667	68.899
MSE	0.0098	0.0190	0.0278	0.0358	0.0431	0.0029	0.0056	0.008

Fig 7. PSNR and MSE of all the images

Next we take a new image that is corrupted by unknown noise

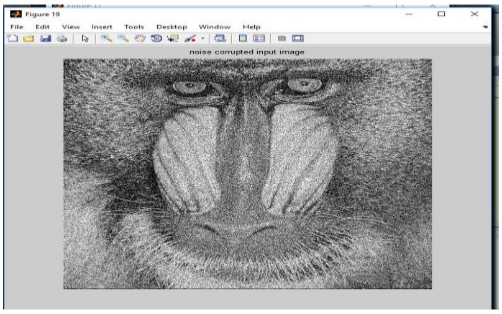


Fig 8. New corrupted image

Estimate PSNR and MSE parameters of this image and thereby estimate the type of noise present in new image based on that

	SP-10%	SP-20%	SP-30%	SP-40%	SP-50%
PSNR	73.7949	70.7934	69.1073	67.9010	66.9573
MSE	0.0027	0.0054	0.0080	0.0105	0.0131

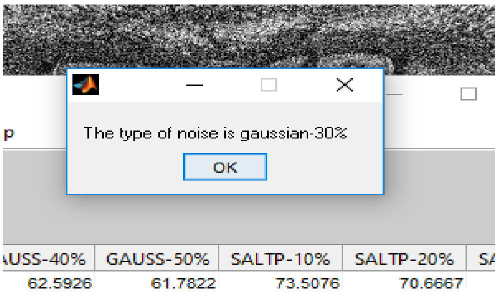


Fig 9. Estimating the type of noise

Applying adaptive subband thresholding technique to denoise the image corrupted by Gaussian noise.

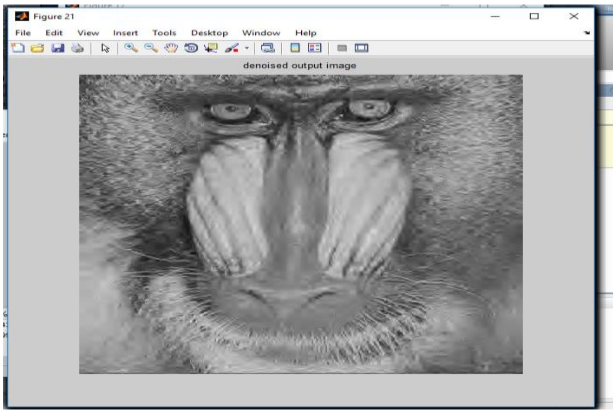


Fig 10. Denoised output image

VIII. PSNR AND MSE CALCULATIONS

The tabulated results of PSNR and MSE calculations of various images when we add different noises such as Gaussian, Salt and Pepper and Speckle ranging from 10% till 50% are given as below:

Table 1: PSNR and MSE for different levels of Gaussian Noise

	Gauss-10%	Gauss-20%	Gauss-30%	Gauss-40%	Gauss-50%
PSNR	68.1843	65.3097	63.7179	62.6076	61.7698
MSE	0.0099	0.0191	0.0276	0.0357	0.0433

Table 2: PSNR and MSE for different levels of Salt and Pepper Noise

	SAP-10%	SAP-20%	SAP-30%	SAP-40%	SAP-50%
PSNR	73.4099	70.5822	68.8359	67.6555	66.5318
MSE	0.0030	0.0057	0.0085	0.0112	0.0145

Table 3: PSNR and MSE for different levels of Speckle Noise

	UNKNOWN
PSNR	63.5972
MSE	0.0284

Table 4: PSNR and MSE of Image corrupted with unknown noise

IX. COMPARISON OF PERFORMANCE PARAMETERS

Table 5: PSNR comparison of various algorithms

σ	Complex wavelet	Neural network	Wavelet Pack thresholding	DCT	Adaptive Subband thresholding
10%	28.231	45.997	36.20	45.923	66.7588
20%	27.184	43.173	34.897	42.355	64.5739
30%	26.191	42.956	33.7692	41.267	63.5972
40%	22.325	40.349	31.337	40.032	62.2503
50%	18.907	38.923	28.168	39.428	61.4932

As we can see in the tables given above the PSNR goes on decreasing as we go on increasing the noise level that has to be added. And it can also be seen that our proposed framework gives a better PSNR performance when compared to other existing algorithms.

X. CONCLUSION

We have designed a package algorithm that at first estimates the type of noise present in an image corrupted by unknown noise and then denoises the image that is corrupted by Gaussian noise. we have evaluated and compared performances of modified denoising method and the local adaptive wavelet image denoising method. These methods are compared with other based on PSNR (Peak signal to noise ratio) between original image and noisy image and PSNR between original image and denoised image. Simulation and experiment results for an image demonstrate that MSE of the local adaptive wavelet image denoising method is least as compare to modified denoising method and the PSNR of the local adaptive wavelet image denoising method is high than other methods. Therefore, the image after denoising has a better visual effect.

XI.REFERENCES

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