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EXPLORING IMAGE DE-NOISING TECHNIQUES THROUGH HISTOGRAM-BASED DENOISING METHODS

Mr. Harshit Singh[1], Shivam Kumar[2], Shivam Pandey[3], Mohammad Shadab[4] and Sumit Pandey[5]
[1]Assistant Professor MCA, Dr. Ram Manohar Lohia Avadh University Ayodhya U.P
[2]Research Scholar MCA, Computer Application Department, Dr. Ram Manohar Lohia Avadh University Ayodhya U.P
[3]Research Scholar MCA, Computer Application Department, Dr. Ram Manohar Lohia Avadh University Ayodhya U.P
[4]Research Scholar MCA, Computer Application Department, Dr. Ram Manohar Lohia Avadh University Ayodhya U.P
[5]Research Scholar MCA, Computer Application Department, Dr.Ram Manohar Lohia Avadh University Ayodhya U.P
[1]harshitsingh@rmlau.ac.in, [2]shivamg707@gmail.com, [3]shivamteam25@gmail.com,
[4]mo.shadab.9795@gmail.com and [5]pandaysumit7278@gmail.com

ABSTRACT
Image de-noising is a classical yet fundamental problem in low level vision, as well as an ideal test bed to evaluate various statistical image modeling methods. The restoration of a blurry or noisy image is commonly performed with a MAP estimator, which maximizes a posterior probability to reconstruct a clean image from a degraded image. A MAP estimator, when used with a sparse gradient image prior, reconstructs piecewise smooth images and typically removes textures that are important for visual realism. One of the most challenging problems in image de-noising is how to preserve the fine scale texture structures while removing noise. Various natural image priors, such as gradient based prior, nonlocal self-similarity prior, and sparsity prior, have been extensively exploited for noise removal. The de-noising algorithms based on these priors, however, tend to smooth the detailed image textures, degrading the image visual quality. To address this problem, we propose a texture enhanced image de-noising (TEID) method by enforcing the gradient distribution of the de-noised image to be close to the estimated gradient distribution of the original image. Another method is an alternative de-convolution method called iterative distribution reweighting (IDR) which imposes a global constraint on gradients so that are constructed image should have a gradient distribution similar to a reference distribution.

IndexTerms - Types of noise, image de-noising, image deblurring, Comparison, Proposed Algorithm.

INTRODUCTION
Image de-noising is to estimate the latent Clean image x from its noisy observation y. One commonly used observation model is y = x + v, where v is additive white Gaussian noise. Image de-noising is a classical yet still active topic in image processing and low level vision, while it is an ideal test bed to evaluate various statistical image modeling methods.

Image de-noising is the process of removing noise from images. It has remained a fundamental problem in the field of image processing. Digital images play an important role in daily life applications like satellite television, magnetic resonance imaging, computer tomography, geographical information systems, astronomy and many other research fields. While we cannot completely avoid image noise, we can certainly reduce them. The image noise is removed usually by image smoothing operation.

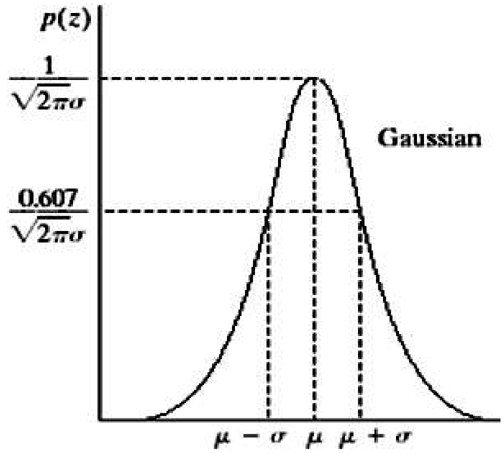

Figure 1 Gaussian Noise Graph

There are two basic approaches to image de-noising, namely spatial filtering and transform domain filtering. Spatial filters operate on a set of pixels related to a given pixel, usually by a sliding window. The window (or kernel) is usually square but can be any shape. Transform domain filters, in general, change the basis of signal space to aid some processing on the image data. Examples of transform domain filtering are Fourier transform and wavelet transform.

TYPES 0F NOISE

Amplifier noise (Gaussian noise):

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise), including that which comes from the reset noise of capacitors ("kTC noise"). Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel.

Salt-and-pepper noise:

Fat-tail distributed or "impulsive" noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. It can be mostly eliminated by using dark frame subtraction and interpolating around dark/bright pixels.

Shot noise

The dominant noise in the lighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level. This noise is known as photon shot noise. Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which is usually not very different from Gaussian.

In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise "or "dark-current shot noise". Dark current is greatest at "hot pixels" within the image sensor. The variable dark charge of normal and hot pixels can be subtracted off (using"dark frame subtraction"), leaving only the shot noise, or random component, of the leakage. If dark-frame subtraction is not done, or if the exposure time is long enough that the hot pixel charge exceeds the linear charge capacity, the noise will be more than just shot noise, and hot pixels appear as salt-and-pepper noise.

Quantization noise (Uniform Noise):
The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. It has an approximately uniform distribution. Though it can be signal dependent, it will be signal independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied.

IMAGE DENOISING METHODS

BM3D Image De-noising:
BM3D is a recent de-noising method based on the fact that an image has a locally sparse representation in transform domain. This Sparsity is enhanced by grouping similar 2D image patches into 3D groups.

A Block Matching Algorithm (BMA) is a way of locating matching blocks in a sequence of digital video frames for the purposes of motion estimation. The purpose of a block matching algorithm is to find a matching block from a frame in some other frame, which may appear before or after. This can be used to discover temporal redundancy in the video sequence, increasing the effectiveness of interface video compression and television standards conversion. Block matching algorithms make use of an evaluation metric to determine whether a given block in frame matches the search block in frame .

Spatial Filtering:
I. Non-Linear Filters: With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible.

II. Linear Filters: A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise.

VisuShrink Thresholding Technique:
VisuShrink de-noising is used to recover the original signal from the noisy one by removing the noise. In contrast with de-noising methods that simply smooth the signal by preserving the low frequency content and removing the high frequency components, the frequency contents and characteristics of the signal would be preserved during VisuShrink de-noising.

SURE
This de-noising method is based on Stein's Unbiased Risk Estimate37 and is applied to the whole wavelet coefficient vector, i.e., the thresholding is performed on each scale j. The SURE method is a hard thresholding approach where the major work is invested in finding the right threshold for the different scales.

Maximum a posteriori estimation
A maximum a Posteriori probability (MAP) estimate is a mode of the posterior distribution. The MAP can be used to obtain a point estimate of an unobserved quantity on the basis of empirical data. It is closely related to Fisher's method of maximum likelihood (ML), but employs an augmented optimization objective which incorporates a prior distribution over the quantity one wants to estimate. MAP estimation can therefore be seen as a regularization of ML estimation.

MAP estimates:
1. Analytically, when the mode(s) of the posterior distribution can be given in closed form. This is the case when conjugate priors are used.

2. Via numerical optimization such as the conjugate gradient method or Newton's method. This usually requires first or second derivatives, which have to be evaluated analytically or numerically.

3. Via a modification of an expectation-maximization algorithm. This does not require derivatives of the posterior density.

4. Via a Monte Carlo method using simulated annealing.

LITERATURE STUDY

The literature review encompasses a wide array of research studies focusing on image denoising techniques, showcasing innovative approaches and methodologies aimed at enhancing image quality and reducing noise in various applications.

Jiang et al. [1] introduce a self-supervised high-dimensional magnetic resonance image denoising method using super-resolved single noisy images, emphasizing the importance of utilizing advanced techniques for denoising complex medical images. Mohammed and Punniakodi [2] conduct a comprehensive study on medical image denoising using convolutional neural networks, highlighting the role of deep learning in achieving superior denoising results.

Peng et al. [3] explore self-supervised signal denoising for magnetic particle imaging, focusing on innovative techniques for denoising signals in specific imaging modalities. Gupta et al. [4] propose a medical image denoising approach using convolutional autoencoder with shortcut connections, showcasing the effectiveness of neural network architectures in denoising medical images.

Mishro et al. [5] conduct a survey on state-of-the-art denoising techniques for brain magnetic resonance images, providing valuable insights into the latest advancements in denoising methodologies. Razavi et al. [6] combine non-data-adaptive transforms for optical coherence tomography (OCT) image denoising, demonstrating the efficacy of iterative basis pursuit in denoising OCT images.

Herbreteau and Kervrann [7] present the NL-Ridge approach, offering a unified view of unsupervised non-local methods for image denoising, highlighting the significance of non-local methods in achieving robust denoising outcomes. Feng and Wang [8] propose an image denoising algorithm based on improved wavelet threshold and non-local mean filtering, showcasing the benefits of combining different denoising techniques for enhanced performance.

Guo et al. [9] introduce an image denoising and colorization approach based on the plug and play framework, emphasizing the importance of incorporating color information in denoising algorithms. Kattakinda and Rajagopalan [10] explore unpaired image denoising, addressing challenges associated with denoising images without paired clean data.

Yang and Chen [11] propose an adaptive iterative low-rank approach for real image denoising, showcasing the effectiveness of low-rank methods in denoising real-world images. Ling et al. [12] introduce a dictionary-learning-based denoising algorithm with a log-regularizer for MR images, highlighting the role of dictionary learning in achieving accurate denoising results.

Song et al. [13] present a grouped multi-scale network for real-world image denoising, showcasing the benefits of multi-scale approaches in handling complex noise patterns. Pravina and Shunmugan [14] conduct a survey on image denoising methods, providing a comprehensive overview of different denoising techniques and their applications.

Parihar et al. [15] propose a hybrid approach for image denoising using an explicit guided filter and collaborative Wiener filter, showcasing the efficacy of combining multiple denoising techniques for improved denoising outcomes. These studies collectively contribute to the advancement of image denoising techniques, offering diverse perspectives and innovative solutions to address the challenges of noise reduction in various imaging applications.

PROPOSED ALGORITHM

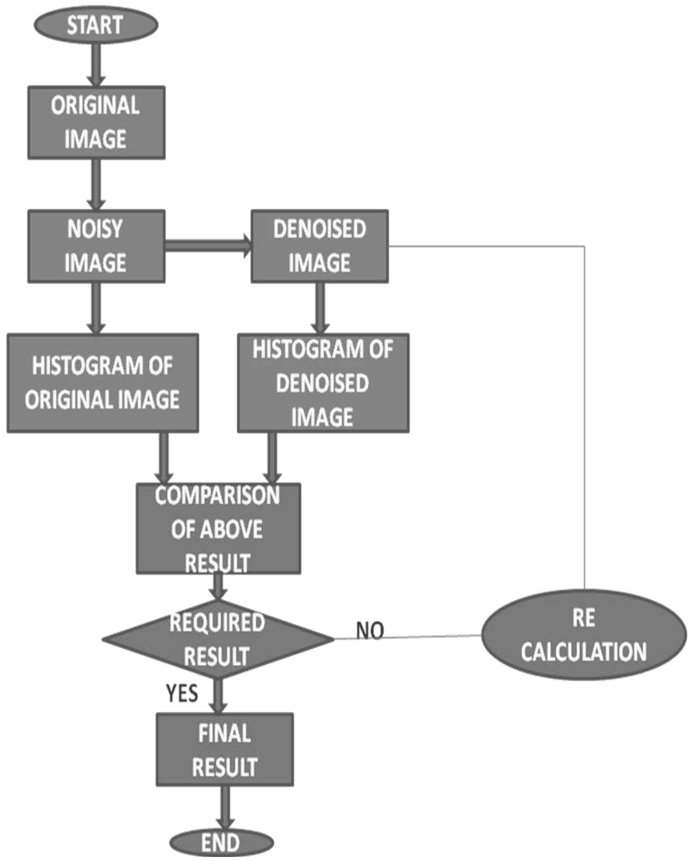

Figure 2 Proposed Flow

The Algorithm is shown in above figure. It includes Original Image, Noisy Image, De-noised Image, the Histogram of Both Noisy and De-noised images, their comparison block and Result.

MATLAB standard image is used as original image. Noisy Image, De-noised Image can be obtain from this Original Image using MATLAB coding. Then Histogram of both images also obtain using MATLAB. Then Results of both histogram are compared for better value of Noise Variance and PSNR(Peak Signal to Noise Ratio).

If Obtain Result is with better PSNR and Variance then it is the final result otherwise Parameters are Re calculated and that result is taken as a De-noised image. And again the same process of taking the histogram and comparison of both. This process is continuous until the Better result is obtained.

RESULTS ANALYSIS

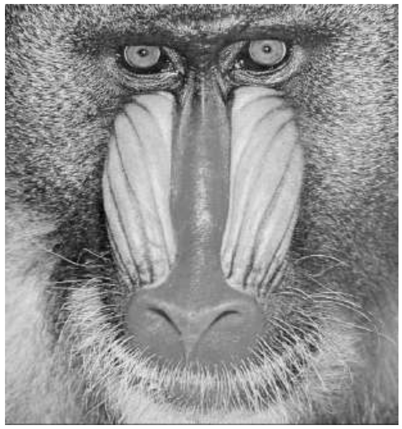

Figure 3 Original Image

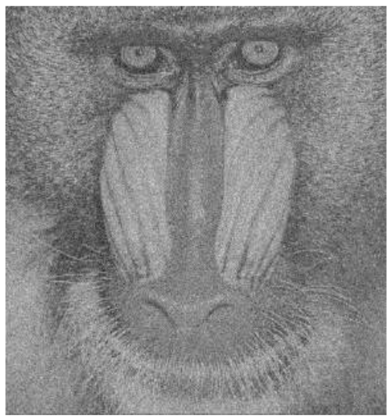

Figure 4 Noise=40 Image

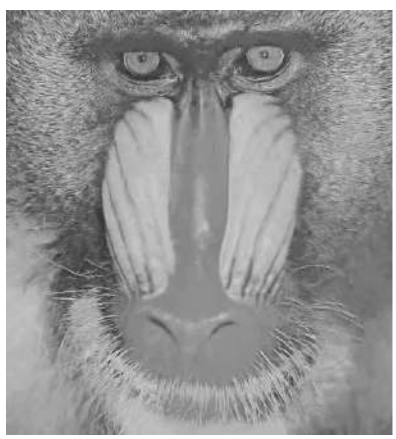

Figure 5 Denoise Noise=40 Image

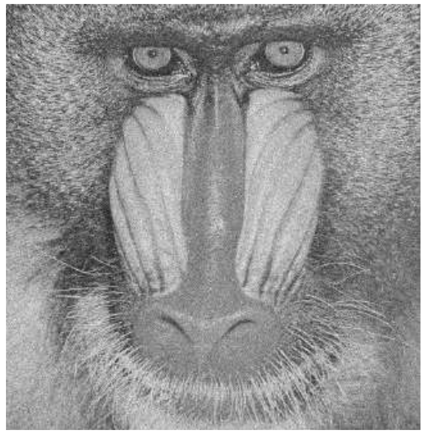

Figure 6 Noise=20 Image

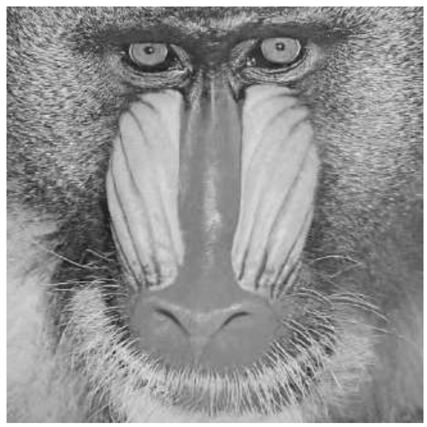

Figure 7 Denoise Noise=20 Image

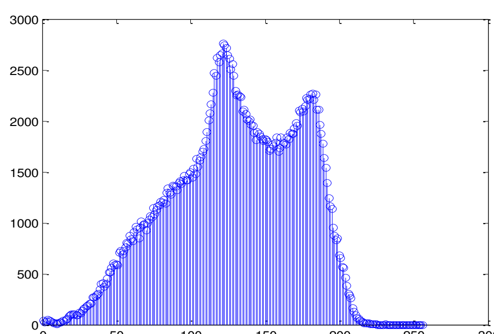

Figure 8 Histogram of Original Image

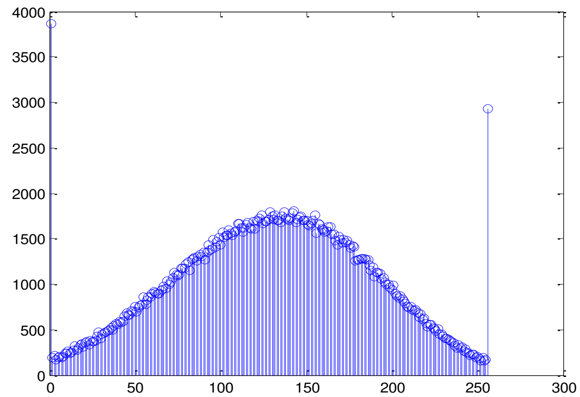

Figure 9 Histogram of Noisy Image, Noise=40

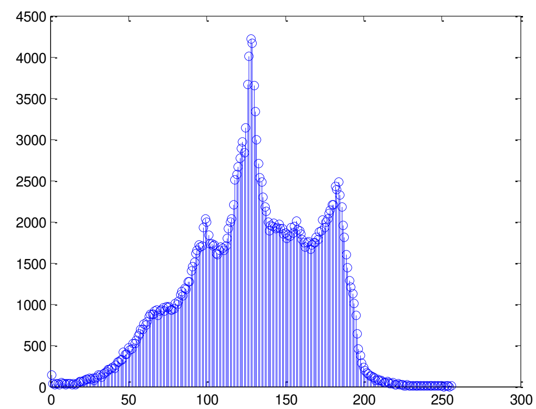

Figure 10 Histogram of De-Noised Image, Noise=40

CONCLUSION

The Techniques which are being available like gradient based prior, nonlocal self-similarity prior, and sparsity prior, yet not able to give satisfactorily the Result which are required for texture structure preservation of images. The Technique Gradient Histogram Preservation is able to produce remarkable result to some extent.

As per one of the Reviewed paper above stated technique can be useful for image de-noising with preservation of texture content, which will be carry forward as a part of dissertation work. According to algorithm Noisy image and De-noised image have been created using MATLAB coding, and further the Histogram are obtained respectively.

With Texture structure Preservation without disturbing the detailed information GHP can be extend to image deblurring, super resolution and other image reconstruction tasks.

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AUTHOR INFORMATION

Harshit Singh is an Assistant Professor in the MCA Department at Dr. Ram Manohar Lohia Avadh University, Ayodhya, U.P.

Shivam Kumar is a Research Scholar in the MCA Department at Dr. Ram Manohar Lohia Avadh University, Ayodhya, U.P.

Shivam Pandey is also a Research Scholar in the MCA Department at Dr. Ram Manohar Lohia Avadh University, Ayodhya, U.P.

Mohammad Shadab, is also a Research Scholar, is part of the MCA Department at Dr. Ram Manohar Lohia Avadh University, Ayodhya, U.P.

Sumit Pandey is a Research Scholar in the MCA Department at Dr. Ram Manohar Lohia Avadh University, Ayodhya, U.P.