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Additive and Multiplicative Noise Removal by using Gradient Histogram Preservations Approach

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ABSTRACT
Image denoising is a traditional yet essential issue in low level vision. Existing denoising technique denoise image but these techniques doesn't concern about multiplicative noise removals. Due to that image texture are not preserved and PSNR value does not properly improved. Image denoising technique uses a novel Gradient Histogram Preservation (GHP) algorithm which preserves image quality. Presently, this technique denoises only additive noise removal. It cannot be applied to non-additive removal, such as multiplicative, Poisson noise and signal-independent noise and it also takes more time in calculations. Since both the noises are dissimilar in nature therefore it is difficult to eliminate both the noises by using single filter. To solve the above issue ,in this paper a novel GHP approach is used to remove additive white Gaussian noise (AWGN) effectively. Since speckle noise is multiplicative in nature; it is converted into additive noise by logarithmic transformation method before apply GHP algorithm. In this paper we use the approach that is to acquire a logarithmic transformation, calculate a covariance matrix of the transformed data, generate random number which follows mean zero and variance/covariance c times the variance/covariance computed in the previous step, then take antilog of the normalized data and apply novel technique using, Fast Fourier Transfer (FFT), Gaussian filter, local content metrics texture ,Iterative Histogram Specifications (IHS) which can denoise both types of noise removal, additive and non-additive noise removal and also takes less calculation time.. In image processing FFT is used in a wide variety of applications, like image analysis, image reconstruction, image filtering and image compression . Gaussian separating is utilized to obscure pictures and evacuate clamor. The proposed algorithm offers to remove the multiplicative noise and improves the visual quality of images.

Keywords
Multiplicative noise, Texture, histogram specifications, sparse matrix representations, local content matrix

1. INTRODUCTION
In general, images are corrupted by noise during image acquisition and transmission which are the principle sources of noise. In image processing step [1, 2], noise plays a vital problem. Noise is a major factor in degradation of the quality of images. To eliminate noise is very vital problem before following any image processing jobs. There are various image denoising approaches are used whose objective is to estimate the clean image P from its noisy observation R. We find the original image P through the reference the noisy image Y. The noisy observation P is defined as: R= P+Q; where Q is additive white Gaussian noise (AWGN) [3], [4], [5], [7].

There are many effective methods to tackle this problem. Therefore, image denoising has been one of the most important and widely studied problems in image processing and computer vision. Many researchers have achieved a mile stone to build up algorithms to reduce or remove noises from noisy image. The major goal of image denoising is to get rid of the noise successfully while preserving the details of the original image as much as possible. Among the most famous ones are variational method which is based on the idea to guess a "trial " wave function for the problems which consists of some adjustable parameters known as "Vatriational Parameters".

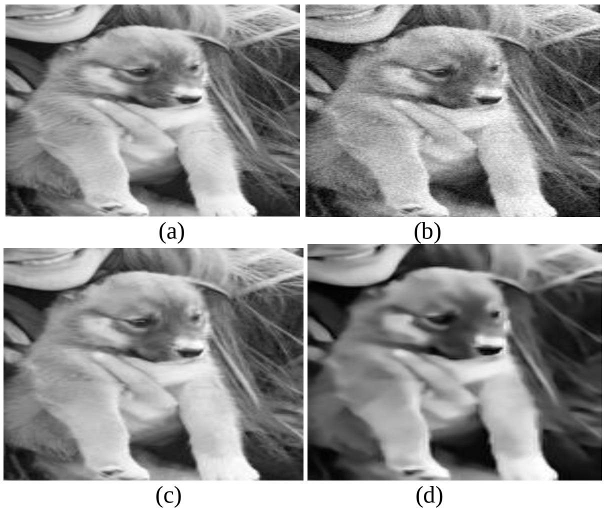


Fig. 1: (a) A cropped image with hair textures; (b) noisy image (c) Denoised image by the GHP method (if noise is additive) (d) Denoised Image by the proposed method (if noise is speckle)

In this paper, we worried on the issue of multiplicative clamor evacuation. Especially we are disposing of commotion from SAR pictures .According to [9] and different references, the clamor in the watched SAR pictures is a sort of multiplicative commotion which is called non-added substance clamor (spot noise).And the picture arrangement model is R = PQ, where R is the uproarious picture, P is the first SAR picture, and Q is the clamor which takes after a Gamma Law with mean one. Non-added substance (Speckle) is a standout amongst the most complex picture commotion models. Signal free, non-Gaussian, and spatially ward are properties of spot commotion.

Consequently spot denoising is an exceptionally dubious issue contrasted and added substance Gaussian and measurable descriptors, for example, histogram are more proficient to portray them. Picture inclinations express the vast majority of semantic data in a picture and imperative to the human impression of picture visual quality One normal approach to evacuate or decrease multiplicative commotion is to really change it into an added substance model, and afterward apply the calculation those are well known about the added substance clamor disposal field. The proposed methodology can do this effortlessly by means of taking the logarithm of the information loud picture, sifting, then opposite log change.

R[n]=P[n]Q[n]==>log(R[n])=log(P[n]Q[n])=log(P[n])+log(n])

At this point we have an additive model once more. Now, we can filter by GHP algorithm and to remove or eliminate log (Q[n]), and then simply take log inverse of the result, yielding an estimate of P[n], our true signal.

In this paper it proposed another procedure utilizing Fast Fourier Transform (FFT) [13], Gaussian channel [14], Iterative Histogram Specification (IHS) for GHP and quality measurements inadequate metrics[7] which can at the same time denoise and proposed, which all the while denoise and protect the fine scale composition structures for both sorts of commotion (added substance, multiplicative). The methodology is to take a logarithmic change, figure a covariance lattice of the changed network, create irregular number which takes after mean zero and fluctuation/covariance c time the difference/covariance registered in the initial step, add the commotion to the changed picture grid and apply Gradient histogram conservation calculation and wipe out clamor after then take an antilog of the evaluated information. This paper researches the factual properties of both systems and shows how well they secure the character of those on the document by means of reidentification trials.

In this paper, the proposed methodology utilize wavelet based methods to perform de-noising strategy. Wavelet based methods has been investigated and utilized for spot clamor end. The outcomes acquired by the wavelets based procedures are contrasted and other spot clamor lessening systems to show its higher execution for dot commotion disposal.

In this paper, the proposed methodology use wavelet based techniques to perform de-noising procedure. Wavelet based techniques has been explored and used for speckle noise elimination. The results obtained by the wavelets based techniques are compared with other speckle noise reduction techniques to demonstrate its higher performance for speckle noise elimination.

2. RELATED WORKS

With the rapid growth of modern imaging devices and their more and more wide applications in our daily life, there are increasing the requirements of novel denoising algorithms for higher image visual quality. Image denoising methods can be grouped into two categories: Model-based routines and learning-based systems.

Most denoising techniques remake the perfect picture by misusing some picture and commotion former models, and fit in with the first classification. Learning-based systems endeavor to take in a mapping capacity from the uproarious picture to the perfect picture [19], and have been accepting impressive exploration premiums [20], [21]. Here we quickly audit those model-based denoising techniques identified with our work from a perspective of common picture priors. Thinks about on common picture priors mean to discover suitable models to depict the attributes or measurements (e.g., appropriation) of pictures in some area. One delegate class of picture priors is the slope former in view of the perception that normal pictures have an overwhelming tailed conveyance of inclinations. The usage of point prior can be taken after back to 1990s when Rudin et. [4] proposed an aggregate variety (TV) model for picture denoising, where the inclinations are really demonstrated as Laplacian dissemination. .Another comprehended previous model, the mix of Gaussians, can similarly be used to inexact the dissemination of picture inclination [16], [22]. What's more, hyper-Laplacian model can all the more precisely describe the overwhelming tailed appropriation of angles, and has been broadly connected to different picture reclamation errands [17], [18], [23]–[25

Tomasi et al. (1998) implemented a bilateral filter that smoothes images as well as preserving edges. It is simple and non-iterative method. But it is difficult to analyze bilateral filter due to its nonlinear nature [6]. Sveinsson et al. (2002) proposed double density discrete wavelet transform (DD-DWT) method that eliminates speckle noise effectively and almost shift invariant [8]. Chen et al. (2008) implemented a novel approach that eliminating salt & pepper noise from the images. But this is not performs on impulse techniques [10]. El-Shehaby et al. (2009) introduced dual-tree complex wavelet transform (DT-CWT) to overcome the limitations of the traditionally decimated discrete wavelet transform (DWT). DWT lacks in directional selectivity [11] and shift invariance properties. Wei (2009) implemented a method of denoising the images that keeps more edge information of image and also improves as well as the PSNR of the denoised image.

After extensive literature survey many different image denoising algorithms, including both local sparsity and NSS based ones, do not preserve fine scale textures while removing noise simultaneously. After that Wangmeng Zuo proposed TEID [12] method to propose a novel and efficient image denoising technique which is based upon gradient histogram preservation (GHP) algorithm.

The histogram of gradient is the better option to describe image textures. It is based on histogram estimation. However, this method works only for additive noisy image. It propose to use Fast Fourier Transform (FFT), Gaussian filter, Local Content metrics and sparse matrix. FFT [13] and logarithmic transformations are more efficient method; it works on the additive and non-additive noise removal in a specified method.

3. PROPOSED WORK

In this image denoising technique is proposed by applying a novel Gradient histogram preservation algorithm to remove AWGN and MWGN (multiplicative white Gaussian noise) which are additive and multiplicative in nature correspondingly. As previous discussed natural image denoising is done by applying following these simple steps:

3.1 Fast Fourier Transformation

FFT is used in many applications, such as image analysis, image reconstruction, image filtering and image constructions . It is more effective technique, often reducing the calculations time by hundreds. It operates by decomposing P point time domain signal into P time domain different isolate signals.. The further step is to estimate the P frequency spectra corresponding to these P time domain signals. Then, the P different isolate spectra are synthesized into a signal frequency spectrum. This technique is mainly used to eliminate the sinusoidal noise. The time taken to estimate a DFT using the FFT is proportional to P multiplied by logarithm of P:

Equation Time = Mufti log2 P

Where, P is the numbers of points. Mffti is proportionality constant.

3.2 Gaussian Filter

It is very effective for reducing the Gaussian noise and it is a smoothing filter in the 2-D convolution operation that is used to eliminate the noise and blur from the natural image. The Gaussian kernel is 2D as:-

The □ (standard deviation) indicates the width of the Gaussian kernel.

3.3 Local Content Metrics

After denoising technique, it is very difficult to calculate how much noise still remains in image, because the effect of denoising varies with the local content in different isolated parts of image. So, we required a metric which that contains an estimate of local noise variance as well.

It is unsupervised way for parameter optimization of image denoising technique.

Algorithm 01: Noise removal and Sharpness Improvement

Input: Input image, Noisy image, Variance

Output: Denoised image

Let I_{org} be the Original Image of size $M \times N$,corrupted by speckle noise of variance $= V$.

Then the noisy image can be given as

$I_{noisy(i,j)} = I_{org}(i, j) + I_{org}(i, j) * V (i, j);$

$I_{noisy(i,j)} == I_{org}(i, j) *(1+V (i, j));$

Where $1 \leq i \leq M$, $1 \leq j \leq N$.

Now our objective is to recover I_{org} from I_{noisy} which is performed as follows:

Step 1: take the log of I_{noisy}

$I'_{noisy} = \log (I_{noisy})$

$I'_{noisy} = \log (I_{org}) + \log (1+V);$

This operation converts the multiplicative noise into much simple additive noise equivalent where $\log (I_{org})$ presents the original image components and $\log (1 + V)$ presents the noisy component. However the pixel values of I'_{noisy} does not falls under the standard pixels value hence normalization or rescaling is required which is performed as follows:

$$I_{noisy}^{norm} = I'_{noisy} * \frac{255}{\log(255)}$$

Step 2: Now as this algorithm uses the texture prevention by maintaining the gradient histogram of the de-noised image. The first approximate the gradient histogram of I_{org} from I_{noisy}^{norm} .

Firstly the previous studies show that the gradient histogram of the natural images follows the heavy tailed distribution hence it can solve it as optimization problem which try to find the best heavy tailed distribution fits over the gradient histogram of I_{noisy}^{norm}.

$$H_{org}^{est} = \underset{H'_{org}}{\operatorname{argmin}} \left\{ \frac{1}{255} \sum_{i=1}^{255} \left| H_{noisy}^{norm}(i) - H'_{org}(i) \right|^2 \right\}$$

Step 3: Now it have the H_{org}^{est}. However we firstly required a de-noised image on which the gradient histogram shrinkage on the basis of H_{org}^{est} can be applied.

The image de-noising in the proposed work is performed by using patch based technique which firstly divides the image into a given number of blocks and then creates the dictionary from it.

B (i) $=(D)\left(I_{norm,}^{noisy}\ i\right)$, where D is the dictionary extractions functions at locations

$B= \{b_1, b_2, b_3 \ldots\ldots\ldots\ldots\ldots\ldots b_k\}$, where k is the total number of blocks;

Once get the dictionary we can create the de-noised image from it by matching the block around the pixel from most suitable block in the dictionary.

$$I_{denoised}(i, j) = \underset{B(i)}{\operatorname{argmin}} \{ D\left(I_{norm}^{noisy}, (i, j)\right) - B(i) \}$$

Step 4: finally got the de-noised image and now the gradient histogram shrinkage can be applied to maintain the texture information in the de-noised image.

$I_{denoised}^{final}$ = funshrinkage (funGradhist ($I_{denoised}$),H_{org}^{est})

The processes from Step3 can be repeated for many times to achieve the better results.

Step 5: Take antilog of above processing metrics and finally obtained denoised image as output

In this way the novel GHP is used for noise removal (additive noise and speckle noise).In this technique .if the noise is additive then directly apply GHP algorithm and if noise is speckle then multiplicative noisy image is transformed into additive noisy image by logarithmic transformations. After that a novel GHP is applied on the transformed noisy image for removing the noise. AND at last apply antilog on estimated image.

The framework of this implemented proposed work is shown by fig2.

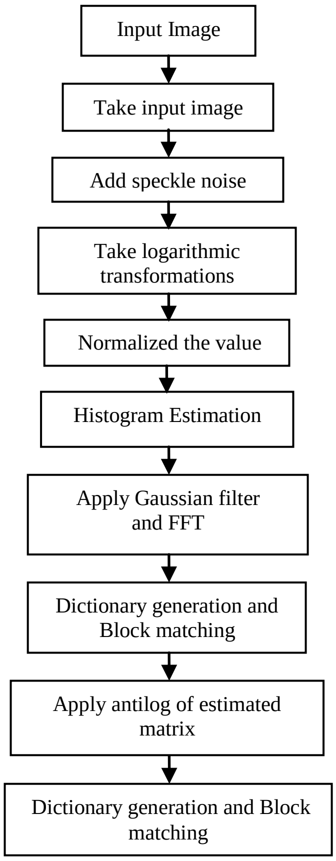


Fig2

4. RESULT ANALYSIS

We have applied TEID and proposed technique on 3 tif images and compared the PSNR.

4.1 TEID

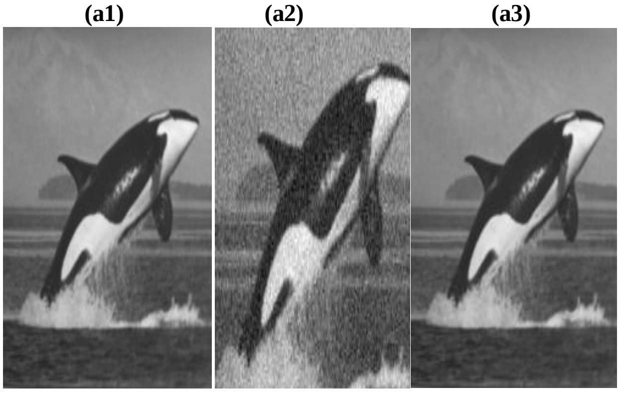
TEID method can only denoise the gray scale image. To perform TEID all images are converted in gray scale image then added additive noise in input image and calculate the PSNR value of denoised images. The summary of experiment is given below in table I.

TABLE I. Teid Experimental Summary

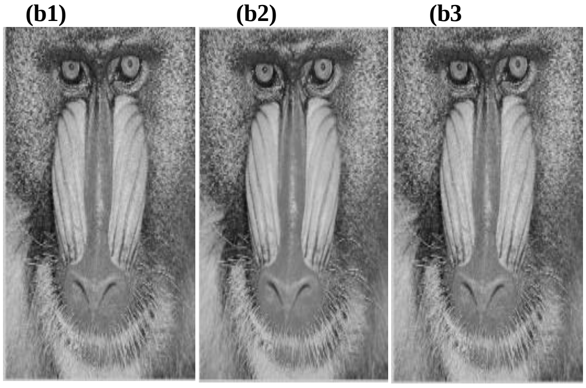
Image	Noisy PSNR(dB)	Denoised Image(dB)
Cameraman.tif	22.0836	34.0132
orka.tif	22.0836	33.0032
Baboon.tif	22.0836	36.0154
Lena .tif	22.0836	32.1045

TEID input images (a1, b1, c1, d1), noisy images (a2, b2, c2, d2) and denoised images (a3, b3, c3, d3) of proposed technique is given below in fig 3:

(a1) (a2) (a3)



(b1) (b2) (b3



(c1) (c2) (c3)

(d1) (d2**)** (d3)

Fig 3

4.2 Proposed Method

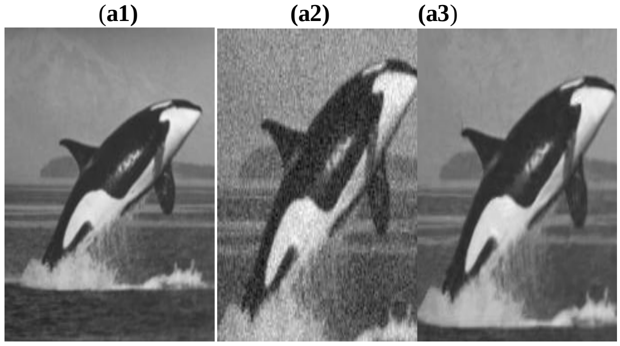
The proposed novel technique can eliminate the additive and as well as multiplicative white Gaussian noise mage. This proposed technique that denoised the image successfully. In this experiment we have added noise in input image and calculate the PSNR value of denoised image. The given below table showing the PSNR value of noisy image and denoised image Result summary is given below in table II.

Proposed Method Experimental Summary

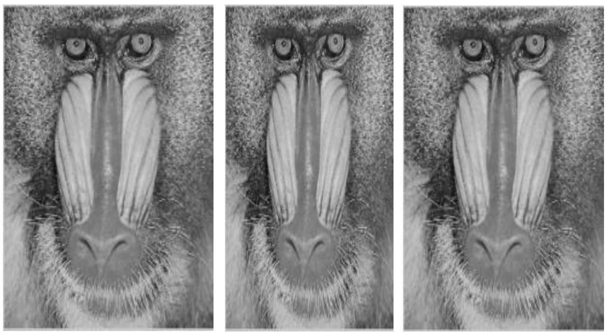
Image	Noisy PSNR(dB)	Denoised Image(dB)
Cameraman.tif	19.7829	29.6928
Orka.tif	28.7807	37.3950
Lena.png	21.1040	31.1675
Barbara.png	25.1782	33.2789

Experimental input images (a1, b1, c1, d1), noisy images (a2, b2, c2, d2) and denoised images (a3, b3, c3, d3) of proposed technique is given below in fig 4:

(**a1) (a2) (a3**)



(b1) (b2) (b3)



(c1) (c2) (c3)

(d1) (d2) (d3)

Fig 4

5. CONCLUSION

In this paper, we presented a new and efficient method using Fast Fourier Transform (FFT), Gaussian filter, logarithmic approach and Local Content metrics. Proposed method uses all above these techniques that denoising the additive and non-additive noise. After implementing with the TEID (Texture enhancement image denoising method) and proposed technique we have summarized the result and compared PSNR value of denoised image. Experimental results verify the effectiveness of the new proposed method. The experimental results demonstrated the effectiveness of the proposed novel method that eliminate additive and multiplicative noise. This proposed novel method also lead to more natural denoising results. As the future perspective can be seen, the proposed technique can be implemented to denoising in video data and live streaming data

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