BI-LEVEL RESTORATION OF AN IMAGE USING MODIFIED JSM

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***Abstract*—This paper provides the loyal restoration of the degraded image in different applications such as to denoise, deblur as well as to infill the image. To obtain such better attributes we use a method of Bi-level restoration process with iteration algorithm which is more strong and governable. The process involves two levels of L1 and L2 Information is considered for topical and nontopical modeling and the degraded pixel is replaced with nonpareil. It produces bestowment to restore the image using modified JSM(MJSM) to overcome the problems during acquisitions and it may due to atmospheric effects in the image processing. The Proposed method produces better results of PSNR than JSM with different transformations.**

***Index Terms*— MJSM, TOPICAL, NONTOPICAL, NONPAREIL, PSNR**

I. INTRODUCTION

Image restoration can be done to improve the quality of the image from the degraded to its to true content. Degradation can be occurred due to acquisitions and unstable voltages in the electronic communication. Many of the filters are used to reduce the degradation properties and to retain better qualities. Noise also one of the reason to degrade the natural pictures which means unnecessary information is added to the required one whereas blur causes smoothening which reduces the quality of information from the image. If there is loss of information i.e., pixel loss then we refill it with infilling technique.

II. EXISTED METHODS

To detect the image degradation problems there are plenty of methods .Some of them use filters to deblur the image or to denoise. Existed methods which provides the effective results in the retainment of edges, sharpness and fine details along with the text information. Some of the existed methods are High pass filters, lowpass filters, TotalVariation denoising technique, NLM method, Morphological methods etc.,

III. AIM

The Aim of the paper is to restore the image to its true content in different cases as from noisy image, to deblur and to infill the degraded version with the nonpareil using MJSM. The existed methods some are useful at pixel level and some are useful at the block level but not at both. In the proposed method we consider the topical such as local pixels closeness and nontopical which considers the block level to know the degree of similarity .To process the MJSM using the iteration algorithm to increase the count of pixel or block after every iteration.

IV. PROPOSED METHOD

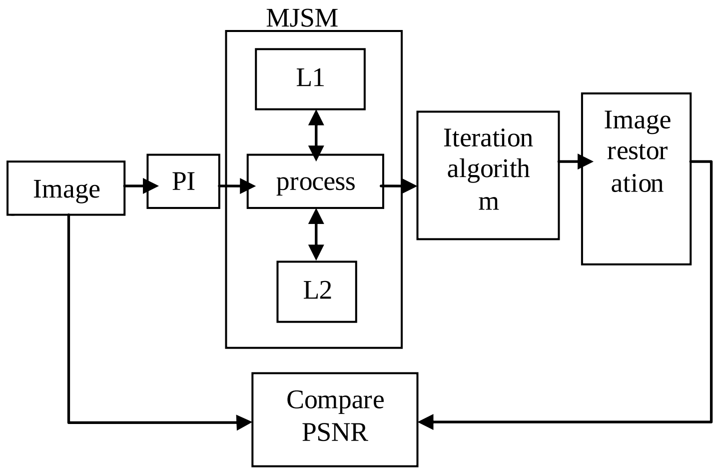
The problem of recovering the images degraded by blurring and impulsive noise is considered .Without loss of generality assume that the image is in space domain (in which the pixel intensity value is changed along with the position) of size mxn represented as

$$y = Hx + n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where

$$H = \begin{pmatrix} H11 & H12 \ldots & H1n \\ H21 & H22 \ldots & H2n \\ . & . & . \\ . & . & . \\ . & . & . \\ Hm1 & . \quad . \ldots & Hmn \end{pmatrix}$$

The block diagram of the restoration with the MJSM is shown as below:



Figure(a) Block diagram of proposed method

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The terms used in the paper are noted below:

MJSM : MJSM process in which we are unifying two levels named as L1 and L2 to acquire great quality of the image with better PSNR values.

L1 : In this level we consider the local block or Pixel value and the closeness among surrounding pixels considering the local smoothness.

L2 : In this level we consider the non topical properties of the image and which is considered as a multi BLOCK level.

PSNR : The ratio which considered as peak signal to Noise Ratio used to compare the refurbished image with the original image to know how much it is retained.(Units : dB)

PI : The Problem Identification can be done based on the matrix operator K which is responsible for the next level of the process.

Bit depth : The bit depth denotes the number of pixels per window. The available bit depth here is eight.

DoS : Degree of similarity is calculated with the help of Euclidean norm is calculated for different coordinates as (x1,y1) and (x2,y2) are the two different pixel intensities in two different positions.

1) Explanation of block diagram

It has been widely recognized that image prior knowledge plays a critical role in the performance of image restoration algorithms. Therefore, designing effective regularization terms to reflect the image priors is at the core of image restoration. The terms utilize local structural patterns and are built on the assumption that images are locally smooth except at edges. This is considered in the level 1(L1). On the other hand, the image property of nonlocal self-similarity should be characterized at level 2 (L2) by a more powerful manner by characterizing both local smoothness and nonlocal self-similarity of natural images in a unified statistical manner with the help of MJSM

The restoration can be done in two domains i.e., image is taken into account in the space domain in which the degree of similarity is considered to compare nonpareil . As a function of (x,y) coordinates image is processed in the space with the position based on the angle theta.

The problem identification shows the way to solve which application that is if the matrix operator H is identity then solve for denoising. If it is Blur operator go for deblurring. If it is mask operator go for infilling technique. After identifying the problem we go for the levels L1 and L2 processing .

In the LEVEL 1 the similarity on the basis of closeness intensity of neighboring pixels is considered. To smoothen the image the topical modeling can be done based on the calculation of following equation:

$$\Psi_{lsm}=\|Du\| \text{ ……………(2)}$$

where D is the horizontal and vertical filter applied to the observed image 'u' and ||.|| is the Euclidean norm which is the integral of the differential operator.

In the LEVEL 2 the go for block wise checking for the non topical similarity in which there are many steps:

Divide an image into n blocks based on the requirement of window size.

Check for the similarity among the divided blocks in which best block is selected.

The best similar blocks in different windows are arranged in a stack .

Apply transformations to the coefficients of the stacked elements of the window.

These transformations are may be DCT,Haar transformsin JSM but in MJSM we used DWT technique which provides better outputs of the search window.

The equation we calculate in the Level 2 is given as

$$\Psi_{nlsm}=\|\Theta u\|=\sum\|T(Zu)\| \text{ …………..(3)}$$

2)Algorithm :

Iteration algorithm used is proposed by Bregmann it is well for noise removal but splitting of the parameters into different terms easily applicable to denoise and deblur.The algorithm used to iterate the process as the checking of blocks increased so that we can iterate upto satisfying the criteria Where iteration number reaches the value of the product of the block size, number of best similar blocks and number of divided blocks.

The following steps are involved in the algorithm;
Input: Observe the image and matrix operator
Initialize: k=0,u(0)=y,b(0)=c(0)=w(0)=x(0)=0
And initialize the optimized parameters μ,Ʈ,λ
Repeat the process for
u(k+1)=argmin1/2||Ku-y||+μ/2||u-w(k)-b(k)||+μ/2||u-x(k)-c(k)||
p(k)=u(k+1)-b(k)
w(k+1)=prox(Ψlsm)p(k)
r(k)=u(k+1)-c(k)
x(k+1)=prox(Ψnlsm)r(k)
b(k+1)=b(k)-(u(k+1)-w(k+1))
c(k+1)=c(k)-(u(k+1)-x(k+1)

Iteration is continued upto required condition is satisfied i.e., upto K reaches bs *c*n
then stop the process.

MJSM (modified JSM)

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Algorithms process data at different scales or resolutions. If we look at a signal (or a function) through a large "window," we would notice gross features. Similarly, if we gaze at a signal through a small "window," we would notice small features. The result in wavelet analysis is to see both the forest and the trees together. Wavelet transforms enable us to represent signals with a high degree of sparsity. This is the principle behind a non-linear wavelet based signal

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estimation technique known as wavelet denoising. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency contents.

In the Level 2 the principal work on denoising is based on degree of similarity i.e., best patch search in the selected window to get the inverse of the image after applying the MJSM the IDWT is applied. The method relies on the fact that noise commonly manifests itself as fine-grained structure in the signal, and WT provides a scale-based decomposition. Motivation to the MJSM idea is based on the assumptions that the decorrelating property of a wavelet transform creates better results than the JSM . Also noise is spread out equally along all coefficients. Further, inserting zeros creates more sparsity in the wavelet domain and one can see a link between wavelet denoising and compression. With JSM we achieve these results at 30 to more number of iterations but in MJSM we can get good results at 5 to 10 iterations is possible with the optimal selection of wavelet matrix mathematically.

Advantages of MJSM

The time consuming for the calculation is very less when compared to JSM.

The better PSNR values will be achieved within 5 to 10 iterations.

The computations are accurate because of wavelet transformations are applying instead of cosine transformations.

For noise Removal:

Adaptive median filtering to detect the noise:

To detect the noise adaptive median filtering technique is used in which the window size is adaptable to the applying MJSM i.e., window size can be reduced or increased to the fine search so it is adaptable .The noisy image pixel is replaced with the median intensity value.

To Remove the Random noisy pixel with the infilling technique:

The method especially useful for the better visual quality and to increase the data sent at one time. In this method we are using triangulation interpolation method for infilling the pixels. Here infilling technique is used to fill the pixel which intensity value is zero. The noisy pixel is made zero and then fill it with best matched pixel with the help of interpolation method.This method is also used to remove the text from the picture images to get clear details of the pixel.Interpolation is the method which creates new set of data points between the two different pixel coordinates of the image. In general method there will be no consideration of properties of the required pixel information. But here we are considering the required pixel information with the help of triangulation basis interpolation method.

The figures we can use are any image with the bit depth 8 and it is applicable to both color and grayscale images. Some of the images we have applied the proposed method to the Barbara image the results will be as shown in the following:

Figure (1)for the uniform blur of Barbara image after MJSM the deblurred image is obtained.

Fig(1): Blurred image Deblurred image

This is for the Gaussian blur image after MJSM deblurred image is obtained.

This is for the motion blur the Barbara images before and after MJSM.

For less iterations we get small change in the psnr value but if we go for higher number of iterations we get the better picture quality along with better results in the psnr value.

The experimental results for the denoising and infilling are also shown as follows:

The figures are for the removal mixed Gaussian and white noise removal after MJSM is Figure (2)

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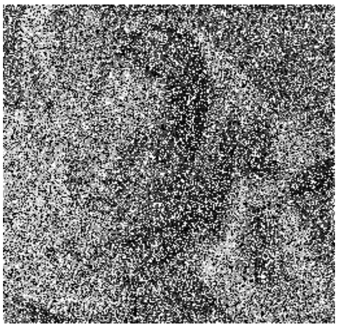
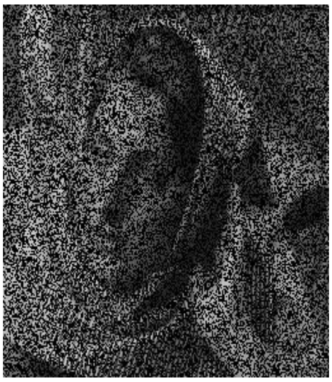


Figure (2) noisy image

Denoised image

The image with random impulse noise in case of infilling is removed after MJSM is as follows:



figure(3) Noisy image

Denoised image

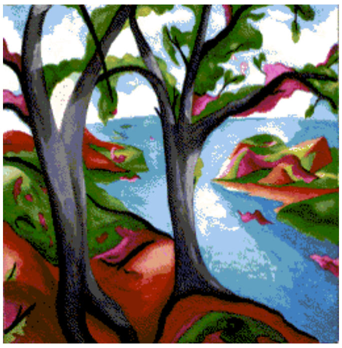
The image with text is obtained after MJSM without text is as shows:

Fig(4) Barbar with text

Without text

These are the figures we have used to check the results of the proposed method :

Fig(5) vegetables



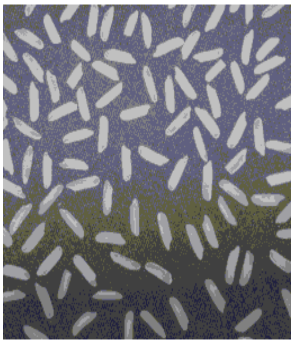
Fig(6) trees

Fig(7) shadow

Fig(8) cameraman

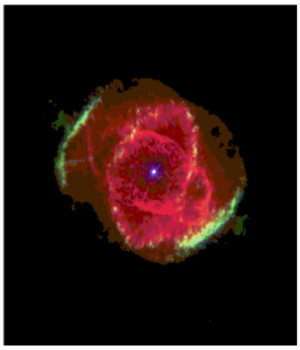
Fig(9) :Sculpt

Fig(10):Fruits



Fig(11):Rice

Fig(12):Lion



Fig(113):Axis

Fig(14):Lena

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Fig (15): Barbara

Fig(16): Text

The noise removal from the image we can go for the infilling technique and also used for the text removal from image.this can be done as take any image of picture mask it with the text information and then apply inpainting technique so that we can retrieve the image only from the text masked image as it is called as texture synthesis.

3)Experimental Results

TABLE 1: The PSNR values of MJSM for Image Deblurring

Blur type	Barbara	Lion	Rice
Uniform	29.26	25.76	22.13
Gaussian	27.03	24.42	20.91
Motion	32.76	28.82	24.15

TABLE 2:The PSNR values of MJSM for Denoising of mixed Gaussian and speckle noise

Images	Denoising	Text removal	Random noise removal
Lion	23.57	28.17	25.58
Barbara	33.91	39.13	38.51
Rice	23.43	29.73	26.89

V. CONCLUSION

The proposed method is more attractive on computation basis and very efficient to retain the image details in three different domains such as for noise reduction, to deblur and to infill the image. The image properties while considering the topical and non topical models are conserved in efficient manner .It is observed that the PSNR values are better for chosen modifications in the transformations which gives better performance.

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