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Image Deblurring and Restoration using Wavelet Transform

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Abstract : This paper proposes image deblurring process used for removal of noise as well as blurred in an image in frequency domain. Wavelet transform is used for the removal of low frequency noise components in degraded image. The proposed noise removal function produces better result than the existing algorithm. It preserves the important information of the image while retrieving.

Keywords : Noise, threshold, wavelet.

1. INTRODUCTION

Digital image processing is the technology which deals with the images and it allows us to acquire, to enhance, and to store the images. The image restoration technique deals with improving the appearance of the poor quality image.

Enhancement is subjective and restoration is objective. Restoration technique is depends on mathematical or probabilistic model of image degradation. Image restoration is now a day's research topic in the field of image processing. Though camera recorded image has accurate representation of the scene, with this image extent of blur information. Image deblurring is used to develop good quality pictures. Many researchers are working on the image deburring problem to restore good quality image. The wavelet analysis is used in recent years over Fourier transform because it has some major advantages. Image deblurring can analyze by following example, consider the input image, degraded with the blurring or degradation function ('typically used here is the motion blurr'). The degraded image can be processed with the various filters and output obtained will be the restored image which can describe the original image successfully as shown in figure 1.

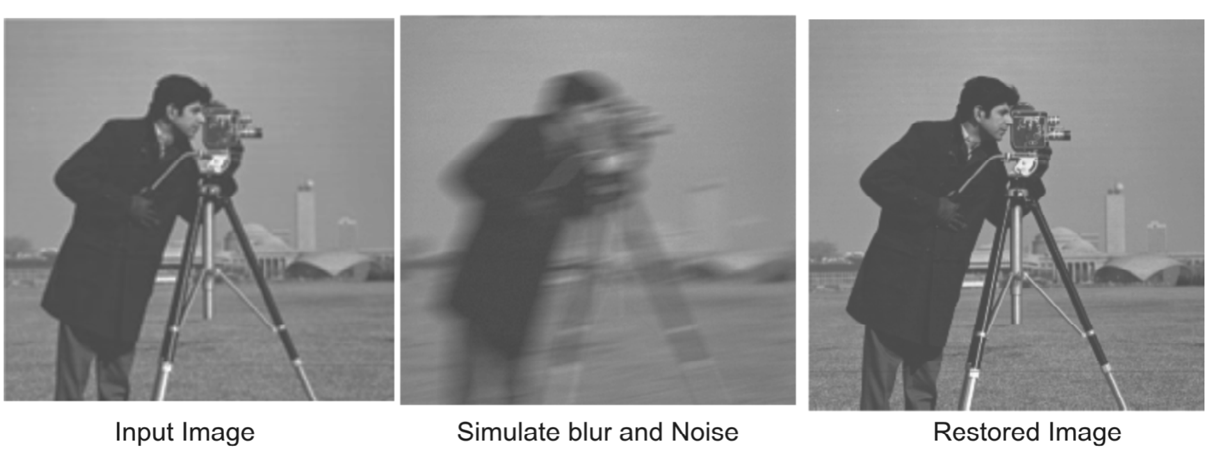

Fig. 1. Blurred/deblurred image.

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A solution to the above problem is a restoration of the blurred image called deblurring. Deblurring can be done with various algorithms such as deconvolution algorithms and filtering algorithm. There are various filters available for deburring such as Wiener filter, Regularized filter, Lucy Richardson filter and using Blind Deconvoution algorithm. While image deblurring, it has been observed and compare the results using Wiener filter, Regularized filter, Lucy Richardson filter and using blind Deconvolution algorithm. This paper consist a method for deblurring of image which makes use of the popular Wavelet transform has Wavelet shrinkage and thresholding technique is used to restore the blurred image to get an restored image having better visual and statistical properties [1] [2] [3] [4].

This paper is organized as introduction in chapter 1. Image debluring methods explain in chapter 2. Thresholding technique is described in chapter 3. Results with variety of images are elaborate in chapter IV.

2. IMAGE DEBLURRING METHOD

In an image deblurring process, input blurred image produces original image. It is the process of removal of blurr and noise presents in an image. Input is processed by means of degradation function and then further processed in frequency domain. The process of deblurring is expresses as shown figure 2.

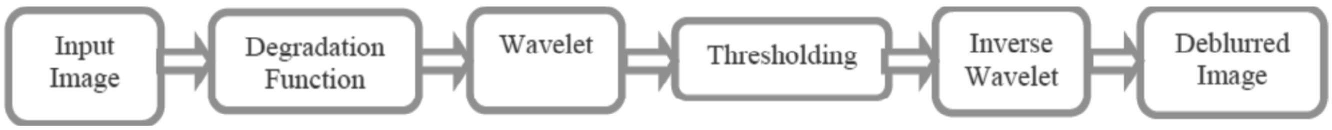


Fig. 2. Image deblurring process.

In the degradation process an input image is degrade using noise term and degrading function to produce a degrade image. A non-stationary signal analysis carried using the Fourier transform or the Short time Fourier transform does not give satisfactory results. Better results can be obtained using wavelet analysis. The discrete wavelet transform (DWT) consist of various filter banks used for construction of the multiresolution time frequency plane. The DWT uses multiresolution filter banks and wavelet filters reconstructing the signals. Amongst the all discrete wavelets the 2-dimentional HAAR wavelets are the most basic wavelets. Wavelets are basically used for decomposing the image, image decomposition generally leads to the different components which are hidden inside the image, which means the wavelet transform results into the various abstracted coefficients [5] [6] [7] [8]. In general HAAR wavelet is used to decompose image into the four parts that are approximation, vertical, horizontal and diagonal component. In the two dimensional wavelets the decomposition is done in the two standard fashions that are standard decomposition and non standard decomposition. This can be easily understood using figure 3 shown below.

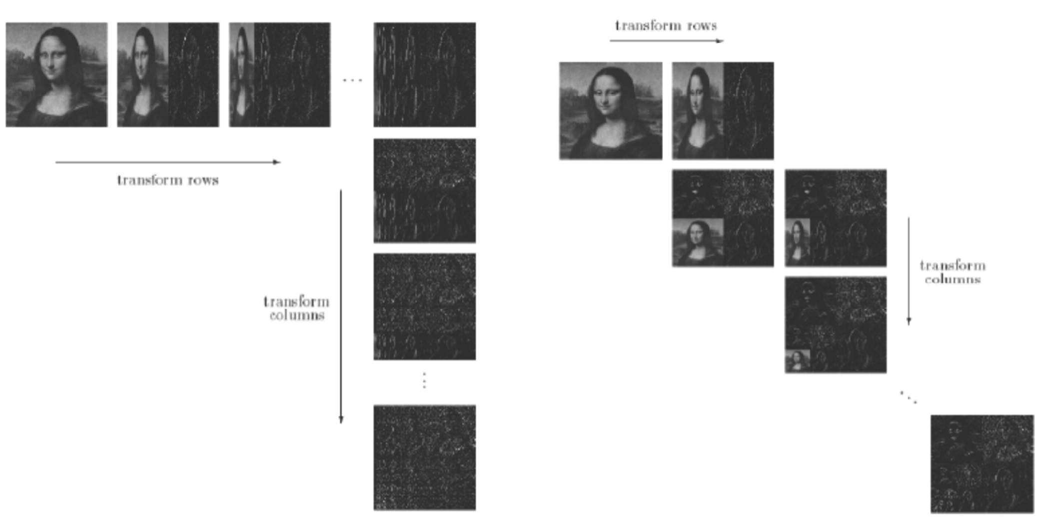


Fig. 3. Wavelet Decomposition

In this example there are two types of decomposition which are given as follows. In the standard decomposition for the n^{th} level decomposition the rows are decomposed first for n times and then the columns are decomposed for n times. But in the non standard decomposition the first step is that first decompose the rows and then the columns. And this step is repeated for n times for n^{th} level decomposition, only approximation coefficients are taken into account.

Wavelet thresholding is used for image de-noising because wavelet provides important information for removing noise in an image. In general wavelet transform is used for energy compaction. It consists of small and large coefficients, first cause of noise and second cause of important features. These small coefficients are generally thresholded without affecting the important information of image. In thresholding smaller coefficients are replaced by zero and by taking inverse wavelet transform on the result to produce reconstructed image with less noise and significant feature. Image restoration is the primary research focuses in the ûeld of image processing. The result of all above processing steps will be the restored image which is visually better and good for analysis point of view.

3. THRESHOLDING

In the recent years most of the researcher works on wavelet based signal thresholding for signal de-noising. Wavelet tool creates appropriate basis for differentiating noisy signal from the original image signal. In general wavelet transform is better for energy compaction due to which the small coefficient and large coefficients are created. They are generated due to noise and later due to important signal features. These coefficients processed using algorithm and threshold it without affecting the important information of the image.

Thresholding is a simple non-linear technique worked on the wavelet coefficient after decomposition. In the thresholding algorithm, the wavelet coefficients are thresholded by comparing existing threshold and the coeeficient value. If the wavelet coefficient is less than the threshold value then set it to zero, if not then keep as it is or modified. The technique of removal of small noisy coefficients and replaced with zero. When applying the inverse wavelet transform on the result produce the original image without noise i.e. reconstruction of the signal. Since the work of Donoho & Johnstone there has been much research on finding thresholds, however few are specifically designed for images [9].

There are two basic types of thresholding such as hard thresholding and soft thresholding. In the hard thresholding, the input is kept same if it is greater than the threshold; otherwise it is set to zero. The hard thresholding technique removes noise while applying it on the wavelet coefficients of the detailed subbands, while keeping the low-resolution coefficients unaltered. If the input that is less than to ä ë is forced to zero otherwise

$$Y = T(X,Y) = \{X \quad \text{where } |X| > \lambda$$
$$= \{0 \quad |X| \leq \lambda$$

The soft thresholding scheme shown in eqn is an extension of the hard thresholding. If the absolute value of the input X is less than or equal to λ then the output is forced to zero. If the absolute value of X is greater than λ then the output is $|y| = |x - 1|$. When comparing both hard and soft shrinking schemes graphically from the above Figures. It can be seen that hard thresholding produces discontinuities at λ and they are more sensitive to smaller changes in the data. The soft thresholding avoid discontinuities as compare to hard threshold therefore it is more stable.

$$Y = T(X,Y) = \{\text{sign}\{X\}(|X| - 1) \quad \text{where } |X| > \lambda$$
$$= \{0 \quad |X| \leq \lambda$$

In practice, soft thresholding is more popular than hard thresholding because it reduces the abrupt sharp changes that occurs in hard thresholding and provides more visually pleasant recovered images. Hard thresholding is the simplest method. Soft thresholding is simple practical mathematical properties and the corresponding theoretical results.

3.1. Selecting an Appropriate Threshold

Given the basic model of the noise given above, it is assumed that the noise to be concentrated in the HH-band of the wavelet domain after resolution into approximations and details by using the wavelet transforms. Thus, the noise in the image can be removed simply by applying a threshold based on an estimate of the noise signal power such that the noise is removed completely and left with a noise-free signal. There are certain assumptions that are made during the application of such a thresholding scheme. One of these is that the signal to noise ratio is more than one. If this condition is not satisfied, then the signal will not be lost when the thresholding is applied to the coefficients. This loss of information is undesirable. Hence, it is imperitive that the peak signal power be greater than the peak noise power.

Thus, the net effect of the thresholding in the HH-band is that the noise signal is suppressed completely while the signal is not affected much. The only affect that this signal has on the image is that the amplitude of the details in the HH-band is reduced by the thresholding amount applied.

Thresholding applied are of two types, namely, global thresholding and level dependent thresholding. In global thresholding, a single threshold is assigned to all the wavelet coefficients irrespective of the resolution level of the wavelet coefficients. Thus, λ remains the same for all

$$d_{j,k}(j = j_0, \ldots, j - 1;\ k = 0, 1, 2, \ldots\ 2^j - 1)$$

In level dependent thresholding, there exists a possibility that the threshold λ_j is different for each resolution level, *i.e.*, the thresholding may be at different values of j. The method of thresholding is, thus, a very effective method of obtaining an estimate of a particular signal from the noisy version of the same signal. This is, however, possible only if the average power of the noise is less than that of the original signal [12] [13] [14].

While the idea of thresholding is simple and effective, the task to determine appropriate value of threshold is not easy. Selection of large threshold λ will shrink almost all the coefficients to zero and may result in over smoothing the image and loosing important information, while selecting a small value of l, will lead to the sharp edges and details being retained but may fail to suppress the speckle. Thus, one of the fundamental problems in wavelet analysis is to select an appropriate threshold.

An approach introduced by Donoho and Johnstone (1994) to denoise in the wavelet domain is known as universal thresholding as given in eqn . The idea is to obtain each threshold li to be proportional to the square root of the local noise variance σ^2 in each subband of a speckle image after decomposition. M is λ the block size in the wavelet domain.

$$\sigma^2 = \sqrt{2 \log (M)}$$

The estimated local noise variance, ó^2 in each subband is obtained by averaging the squares of the empirical wavelet coefficients at the highest resolution scale as given in equation.

$$\sigma^2_{J=0}{}^{N-1} = [1/N \sum (x_1)^2]$$

The threshold of equation is based on the fact that for a zero means *i.i.d.* Gaussian process with variance σ^2, there is a high probability that a sample value of this process will not exceed l. Thus the universal threshold is applicable to application with white Gaussian noise and in which most of the coefficients are zero. In such cases, there is a high probability that the combination of (zero) coefficients plus noise will not exceed the threshold level l [16] [17].

3.2. Existing thresholding METHODS

A. Universal Threshold

As the name in itself suggests, the universal threshold scheme is a global thresholding scheme in which a universal threshold is fixed for all the empirical wavelet coefficients. This was suggested by Donoho and Johnstone. This threshold is given by the following equation.

$$\lambda_u = \sigma\sqrt{2 \log n}$$

The main advantage of this threshold is that the implementation of this threshold in software is quite easy and there is no need for the development of any costly lookup tables. The universal threshold method provides every signal in the wavelet transform consist for removal of noise as per the coefficients and threshold. This is due to the fact that the probability that the noise coefficients in the wavelet domain will have amplitude greater than the threshold given above tends to zero as the sample size tends to infinity. If the threshold value is raised beyond the above value, then the convergence rate of this probability to zero will also increase.

B. Bayes shrink

BayesShrink is an adaptive wavelet thresholding method proposed by Chang, Yu, and Vetterli using a Bayesian estimate of the risk. Threshold calculations depends on the wavelet coefficients but they are described by a generalized Gaussian (GG) distribution with shaping parameter β. There no absolute solution found for this problem, but Chang et al. estimated this threshold to be

$$\lambda_{\text{Bayes}} = \frac{\sigma^2}{\sigma_{xj}}$$

which compares very well to the optimal threshold found numerically. This estimated threshold is generaly indepent of the value of the shaping parameter β, eliminating the need to estimate any other parameters.

3.3. Other Deblurring Methods

3.3.1. A Faster Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems

Total Variation Basics :

The case $p = 1$ (the smallest value of p for which $\|\bullet\|\, p$ is a norm) has received attention in connection with total variation denoising and deblurring of images, when it is used together with first derivatives. The gradient magnitude $y(s, t)$ of the two-dimensional function $x — x(s, \text{t})$ is a new two-dimensional function, defined as:

$$y(s, t) = \|\nabla_x\|_2 = \left\| \begin{bmatrix} x_s \\ x_t \end{bmatrix} \right\|_2$$

Where again it use the notation x_s and x_t to denote, respectively, partial derivatives of x with respect to s and with respect to t. The total variation functional is then defined as

$$\text{J}_{\text{TV}}(x) = \|\gamma\|_1 = \int_0^1 \int_0^1 |\gamma(s,t)|\, dsdt$$

It is seen that if the function $x(s, t)$ represents an image, then the total variation functional $\text{J}_{\text{TV}}(\text{X})$ is a measure of the accumulated size of the edges in the image. In the discrete formulation, the total variation of the image X is given by

$$\text{J}_{\text{TV}}(\text{X}) = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\left(\text{XD}_{1,n}^{\text{T}}\right)_{ij}^2 + \left(\text{D}_{l,m}\ \text{X}\right)_{ij}^2 \right)^{1/2}$$

which is a sum of the 2-norms of all the gradients associated with the pixels in the image X. The total variation deblurring problem then takes the form of a nonlinear minimization problem

$$\min\{\|b - \text{Ax}\|_2^2 + \alpha \text{J}_{\text{TV}}(\text{X})\}$$

where the last, nonlinear term $/rv(\text{X})$ plays the role of the regularization term from the Tikhonov formulation. This minimization problem can be solved by variations of Newton's method.

In wide range of applications linear inverse problems arises. To understand basic linear inverse problem needs to study discrete linear system of the form $\text{A}_x = b + w$, where $\text{A} \in \text{R}m \times n$ and $b \in \text{R}m$ are known, w is an unknown noise (or perturbation) vector, and x is the "true" and unknown signal/image to be estimated. For example, $b \in \text{R}m$ represents the blurred image and $x \in \text{R}n$ is the unknown image, its size is assumed to be the same as that of b ($m = n$). In two dimensional images, b and x are created by stacking columns. The matrix A in this example describes the blur operator, generally in the case of spatially invariant blurs represents a two-dimensional convolution operator. In recent manuscript by Nesterov, has independently investigated a multistep version of an accelerated gradient-like method that also solves the general problem model, like FISTA, is proven to converge in function values as O(1/*k*2), where *k* is the iteration counter. While both algorithms theoretically achieve the same global rate of convergence, the two schemes are remarkably different both conceptually and computationally. In particular, the main differences between FISTA and the new method proposed are that (*a*) on the building blocks of the algorithms, the latter uses an accumulated history of the past iterates to build recursively a sequence of estimate functions ψk (•) that approximates F(•), while FISTA uses just the usual projection-like step, evaluated at an auxiliary point very specially constructed in terms of the two previous iterates and an explicit dynamically updated stepsize; (*b*) the new Nesterov's method requires two projection-like operations per iteration, as opposed to one single projection-like operation needed in FISTA [18][19][20][21][22].

The algorithm worked with constant stepsize. The main difference between the above algorithm and ISTA is that the iterative shrinkage operator pL(•) is not employed on the previous point $xk-1$, but rather at the point yk which uses a very specific linear combination of the previous two points $\{xk-1, xk-2\}$. Obviously the main computational effort in both ISTA and FISTA remains the same, namely, in the operator *pL*. The requested additional computation for FISTA in the steps and is clearly marginal. The specific formula for emerges from the recursive relation that will be established below in Lemma.

3.3.2. Deconvolution using a Gaussian Prior

The simplest way is to solve problem in the frequency domain. Since A is a sum of convolution matrices, its diagonal in the frequency domain. Including priors, however, will pull the solution toward zero, especially in frequencies in which |F(*n*, *w*)| is small. It should also be noted that the response of a derivative filter is larger in the higher frequencies and small in the lower frequencies. Thus, the prior effect will be stronger in the higher frequencies. This is a reasonable thing to do since in those frequencies, the image content is expected to be small and the noise contribution is stronger. In the frequency domain, the deconvolution problem can be solved extremely efficiently the most expensive part being the Fourier transform. The price to pay, however, is that expressing convolution in the frequency domain assumes the convolution operation is fully cyclic and this assumption is wrong along image boundaries. Therefore, applying deconvolution in the frequency domain usually result in artifacts at the image edges. For the application having to clip a narrow strip along image boundaries out of a 2M pixel image is not a huge price to pay.

3.3.2.2. Deconvolution in the spatial domain

To avoid the cyclic convolution assumption it is necessary to include in the convolution matrices Cf ,Cgk only valid pixels (or in other words- to omit rows corresponding to boundary pixels) and thus the convolution matrices will have less rows than columns. The penalty for doing this is that the convolution operation will no longer be diagonal in the frequency domain. The processing can be carried in the spatial domain. However, if the image is large, or if the support of the filters is large, explicitly inverting it. The bottleneck in each iteration of this algorithm is the multiplication of each residual vector by the matrix A. Luckily the form of A enables this to be performed relatively efficiently as a concatenation of convolution operations.

4. RESULT

This paper suggests various methods of deblurring for color and gray scale image. The table 1 shows the result for Lena image which is gray scale for various threshold and proposed threshold and self-organizing map. Table 2 shows the result for the various algorithm and proposed values in terms PSNR. Table 3 represents the result for self-organizing map for various noise density levels. Table 4 shows the results for color image for various threshold function. Table 5 represents PSNR values for color images. Table 6 represents result table for the Self Organizing Map method. Table 7shows the result for Total variation based FISTA algorithm images at various iterations. Table 8 shows the result table For Total Variation Based Deblurring With FISTA its PSNR. Table 9 shows the results for deconvolution algorithm and its PSNR values. Table 10 shows the image results for Deconvolution algorithms

Table 1. Results for Lena image at Various noise density

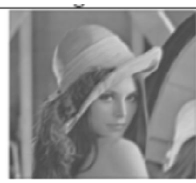
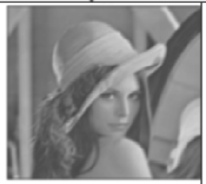
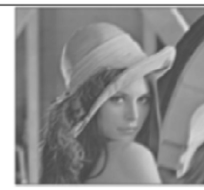
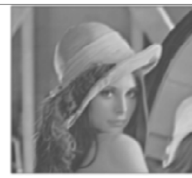
				
Original Image	Blurred Image	Visu shrink: HT	Visu shrink : ST	Bayes thresholding HT
				
Bayes thresholding ST	proposed threshold HT	proposed threshold ST	Self organizing map	

Table 2. Result for shrinking algorithms:PSNR values in dB Lena.

Variance	*Visushrink*		*Bayes shrink*		*New proposed method*	
Noise density	*Hard*	*Soft*	*Hard*	*Soft*	*Hard*	*Soft*
0.001	25.8391	26.3613	25.8771	26.3516	25.7610	26.4382
0.01	20.8919	23.4436	19.3337	23.4090	19.3995	21.7016
0.1	13.1272	16.7146	11.1930	-	11.2042	13.8165
Without noise	27.1416	26.8632	27.1267	26.8735	27.8165	27.3991

Table 3. Result table for Self Organizing Map method

	PSNR	
Noise Density	*Lena*	*Barbara*
0.001	24.8653	22.1675
0.05	24.6466	22.0195
0.01	24.8309	22.1437
0.1	24.1227	21.7685

Table 4. Results for color image for various threshold function

				
Original Image	Blurred Image	Visushrink: Hard thresholding	Visushrink:Soft thresholding	Bayes shrink: Hard thresholding
				
Bayes shrink: Soft thresholding	proposed threshold : Hard thresholding	proposed threshold : Soft thresholding	Restored	

Table 5. Result table for color images.

	PSNR values in dB					
Variance	*Visushrink*		*Bayes shrink*		*New proposed method*	
Mixed fruit	*Hard*	*Soft*	*Hard*	*Soft*	*Hard*	*Soft*
0.001	21.9713	25.0113	20.5379	25.0030	21.5234	25.0141
0.01	21.8695	24.8341	21.1424	24.8270	21.4131	24.8296
0.1	18.0176	19.0418	18.0229	19.0495	17.7851	19.0465
0.000	21.9864	25.0316	20.4656	25.0218	21.5324	25.0225

Table 6. Result table for the Self Organizing Map method

	PSNR values in dB	
Noise Density/Images	*Mixed fruit*	*BaBY*
0.001	**28.2337**	**20.2435**
0.05	**27.7239**	**20.0801**
0.01	**28.1802**	**20.2156**
0.1	**26.6119**	**19.8555**

Table 7. Total variation based FISTA algorithm images at various iterations

				
Original	Blurred	Restored Image (20 iterations)	Restored Image (40) iterations	Restored Image (60 iterations)
				
Restored Image (80 iterations)	Restored Image (100 iterations)	Restored Image (200 iterations)		

Table 8. Result table For Total Variation Based Deblurring With FISTA its PSNR

Sr. No.	*Number of iterations*	*PSNR*
1.	20	77.346
2.	40	76.1115
3.	60	76.1521
4.	80	76.1741
5.	100	6.1728
6.	200	6.1695

Table 9. PSNR Result table For Deconvolution algorithm

No	*Deconvolution Algorithm*	*PSNR values*
1.	Lucy-Richerdson	75.8859
2.	L2 Deconvolution (Varying smoothness weight)	77.1359
3.	L2 Deconvolution in Frequency domain (Varying smoothness weight)	73.4864
4.	Sparse Deconvolution (Varying smoothness weight)	77.1743

Table 10. Image Results for Deconvolution algorithms

				
input	Lucy deconvolution	L2 de convolution	L2 de convolution in frequency domain	Sparse de convolution

4. CONCLUSION

There are limits of conventional methods in image deburring, several drawbacks are seen in the conventional methods. This paper analyzed the various techniques of image deblurring and after analysis It is concluded that the image can be further enhanced by using the wavelet transforms. The various thresholding techniques used to get the better results. These thresholding techniques are applied for both colour and grey level images. It consider PSNR (peak signal to noise ratio) parameter for comparision between the blurred and restored image. The PSNR for the colour image is less compaired to grey level image. For different values of variance, it has calculated respective PSNR values

The existing thresholding technique used are visushrink, bayesshrink it proposes a new method of thresholding, the newhreshold is calculated by considering the various parameters of the image, so new threshold gives a comparable results with that of the conventional thresholding methods. It preserves the important information of the image.

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