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De-noising of gray and color images against multiple noises via offline dictionary

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***Abstract*— The paper De-Noising of Images corrupted in presence of multiple noises via offline dictionary, deals with problem of image restoration which is continuously affected by Impulse Noise (IN) or / and Additive White Gaussian Noise (AWGN) which are commonly occurring noises.The paper envisage implementation of the method to remove mixed noise which commonly occurs in signal processing such as AWGN and IN (AWGN+SPIN, AWGN+SPIN+RVIN). The method includes detection based method, which first detects the noise in the pixel of image then removes mixed noise. Hence such method create more artifacts when mixed noise is too strong. Here soft impulse pixel detection is used via weighted encoding which removes IN and AWGN simultaneously. In this paper Adaptive Median Filter is also used to remove IN with less effort.**

Key Words: AWGN, IN, Mixed noise and weighted encoding

I. INTRODUCTION

Image denoising is one of the important and developing areas in the branch of image processing. Noises are unavoidable during image generation, transmission and reception process, due to which quality of image will be reduced. Unwanted information which are added during acquisition or transmission or reception which destroys the quality of the image is called as "noise".

Image restoration techniques aims at recovering the original images. Images are corrupted by degradation such as linear frequency distortion and noise. This paper is based on image corruption due to noise. Image restoration is defined as the method of elimination of degradation in the image using linear or nonlinear filtering. Ultimate goal is to bring the corrupted image into original form or to improve the quality of the denoised image. Denoising process which is also called as "noise removal" is a challenging task in the branch of image processing. This operation aims at the maximum preservation of fine details, image edges and textures of the original image. For this, knowledge of different types of noise distribution is required [4].

There are many types of noise exist, out of which mainly two types of noise are considered in real time application. These are AWGN and IN. AWGN has heavy tail hence it is a challenging task to de-noise. Impulse Noise has two types of noises ie. Salt Pepper Noise (SPN) and Random Valued Impulse Noise (RVIN). RVIN is not easy to remove due its properties.AWGN is regularly introduced because of the thermal movement of electrons in camera sensors and in other electronic devices. IN is frequently introduced by malfunctioning of the camera sensor pixels, defective memory segments in hardware and transmission error like bit error. In AWGN, each image pixel which is replaced with a value independently sampled from a Gaussian distribution with zero mean, which is going to add with the gray level of the pixel [5]. The image which is corrupted with IN will be having a portion of its pixels exchanged with values of random noise with the remaining pixels unaltered. There are two types of commonly considered IN, Salt and Pepper Impulse Noise (SPIN) and Random Valued Impulse Noise (RVIN). The image which is degraded by SPIN results in bright pixels in dark regions and dark pixels in bright regions. Image which is degraded by RVIN results in noise in any random pixel locations. The main aim of the paper is to implement an effective method for the removal of mixed noise(AWGN+IN) in gray and color image using combination of new Weighted Encoding and Sparse Nonlocal Regularization (WESNR) process.

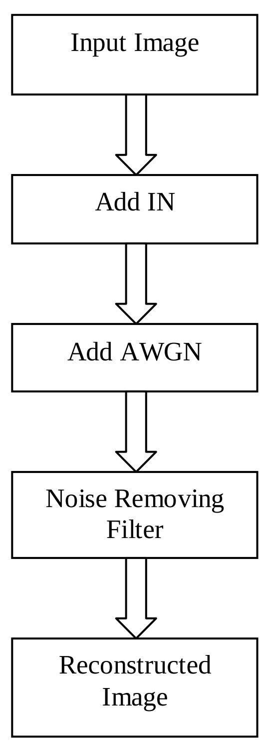

Fig. 2: Process flow in the denoising of image

Image noise is an unavoidable side-effect occurring as a result of image capture, more simply understood as inaudible, yet inevitable fluctuations. In a digital camera, if the light which enters the lens misaligns with the sensors, it will create image noise. Even if noise is not so obviously visible in a picture, some kind of image noise is bound to exist. Every type of electronic device receives and transmits some noise and sends it on to what it is creating.

When the images are transmitted over channels, they are corrupted with impulse noise due to noisy channels. The impulse noise consists of large positive and negative spikes [7]. The positive spikes have values much larger than the background and thus they appear as bright spots, while the negative spikes have values smaller than the background and they appear as darker spots. Both the spots for the positive and negative spikes are visible to the human eye. Also, Gaussian type of noise affects the image. Thus, filters are required for removing noises before processing. There are many filters proposed for the removal of such noise. Like linear smoothing filter, median filter, wiener filter and Fuzzy filter.

In this filtering technique, the three primaries(R, G and B) are filtered separately. It is followed by some gain to compensate for attenuation resulting from the filter. The filtered primaries are then combined to form the colored image. This process is very simple. This approach is shown in figure 1.

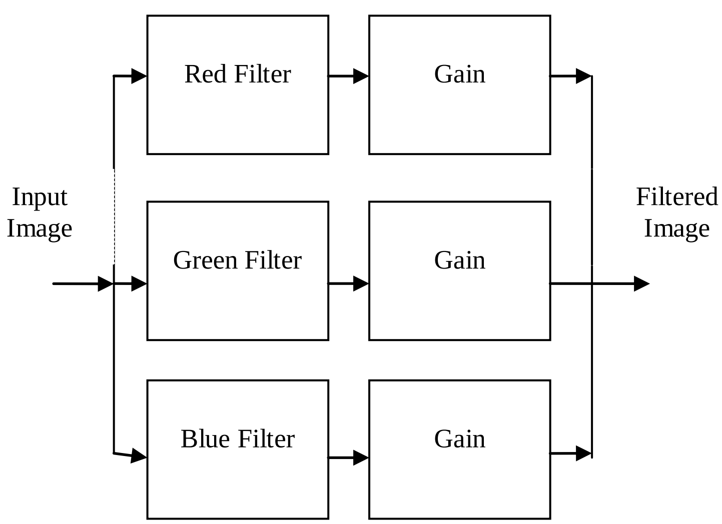

Figure1. Filtering the three primaries separately

II. WEIGHTED ENCODING ALGORITHM

The proposed weighted encoding algorithm results in better performance with respect to mixed noise removal. This method can handle the combination of mixed noise that is, AWGN + SPIN and AWGN + SPIN + RVIN and runs very much faster than any other methods. The superiority in the denoising operation of weighted encoding with respect to other methods is achieved from the unified frame work of weighted encoding operation and sparse nonlocal regularization operation [2].

The paper considers two types of noise. First, the mixture of AWGN + SPIN is considered. For the mixed noise, AMF (Adaptive Median Filter) is used at the initial stage for the removal of SPIN. For the mixed noise AMF is applied over the noisy image *Y* to obtain an initialized image vector denoted as $x^{(0)}$ and then residue '*e* ' is initialized as:

$$e^{(0)} = Y\text{-}x^{(0)} \qquad (2.1)$$

Second, the mixture of AWGN + RVIN + SPIN is considered. For this type of mixed noise AMF cannot be applied directly over the noisy image *Y*. Hence in this case, the residue '*e'* is modified as:

$$e^{(0)} = (Y\text{-}\mu_y)*1 \qquad (2.2)$$

In equation (2.2), 'μ_y' is the median value of all the pixels in the noisy image *Y* and '*1*' is a column vector with all elements value as 1. Then weighted encoding and residual calculation is performed, with the initialized coding residual '$e^{(0)}$'.

III. MATHEMATICAL MODEL

DE-NOISING MODEL

Here mixed noise removal which doesn't detect impulse noise explicitly and which can process AWGN+IN simultaneously.

In the weighted encoding model '*W'* is a diagonal weight matrix and its element 'W_{ii}' is automatically determined and assigned to pixel at location '*i'* which is given in equation (3.1). This weight '*W'* represents similarity between neighborhoods of the each pair of pixels considered. The image pixels which are corrupted with IN will have smaller weights to minimize their effect on the encoding of *Y* with respect to the dictionary 'ϕ', while the weights with uncorrupted pixels will be considered to **l**. In this algorithm, the dictionary 'ϕ' is pre learned from clean natural images. The pixel corrupted by IN having higher coding residuals and it can be used to guide the setting of weight 'W_{ii}' and is inversely proportional to the strength of coding residual [1]. One simple and appropriate equation of 'W_{ii}' is given as:

$$W_{ii} = exp\,(-a\, e_i^2\,) \qquad (3.1)$$

Once '*W'* is calculated as per the equation (3.1), process becomes ready to $\mathbf{l_2}$ normalization technique which also includes sparse coding problem. This is solved by considering many iterations of weighted encoding operation. For next operation, let '***V***' is a diagonal matrix which is initialized as identity matrix and then in the **(k+1)th** iteration, each and every element of diagonal matrix '***V***' is updated as:

$$V_{ii}^{(k+1)} = \lambda / \sqrt{((\alpha^k_i - \mu_i) + \varepsilon^2)} \qquad (3.2)$$

where 'ε' is a scalar and 'α^k_i' is the i^{th} element of coding vector 'α' in the iteration. The parameter 'λ' is regularization parameter, which plays an important role. If the value of 'λ' is zero which means that, there is no noise content. As the 'λ' value increases, shows the noise content in the image. Then 'α' can be written as:

$$\alpha^{(k+1)}=(\phi^T W \phi + V^{k+1})^{-1}(\phi^T W Y-\phi^T W) +\mu \qquad (3.3)$$

After iteratively updating of diagonal matrix '*V*' and 'α ', the actual value of 'α' will be effectively obtained.

PARAMETER SETTING

For good performance parameter setting step plays a major role, to obtain WESNR role all parameter used in algorithm are fixed by Trial method. the two parameter are used to compute the diagonal matrix V: λ and ε, λ is taken as 0.0001 to weaken the role of non-local regularization term which is used in algorithm to remove AWGN It comes to conculsion that if standard deviation for AWGN removal is higher than 10 then λ is assigned as 1 else 0.5 to supress AWGN in preserving image details.ε is assign as small value as 0.1.

DICTIONARY

In this paper it is assumed that the dictionary 'ϕ' is obtained first and later it is used in the algorithm. The selection of dictionary is an important issue of the sparse coding and reconstruction of an image. In particularly, learning dictionaries from natural image patches is an important process in image restoration. In this paper, a set of local PCA dictionaries are considered, offline from five high quality images with respect to original. The image patches are divided into many clusters. Each cluster consists of many patches with similar patterns. A complete set of dictionary can be obtained from the each cluster. PCA technique is used to obtain the dictionary. For the image patches to be coded, the dictionary value which is more relevant is considered with the noise pixel patch to replace.

Total number of 2401 200 patches are extracted from the high quality images and then they are divided into 200 clusters with help of *K-means* clustering algorithm. It is simplest method in which clustering is done by iterative procedure. It clusters the data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with closest mean. Clustering is the technique in which relationship among the patterns of the data set by organizing the patterns into group of clusters such that pattern within a cluster are more similar to each other than patterns belonging to different clusters.

ALGORITHM STEPS:

Input: Generate dictionary 'Φ' over the noisy image *Y;*
Residue 'e' is initialized by
Equations;
$e^{(0)} = Y-x^{(0)}$ and
$e^{(0)} = (Y-\mu_y)*1$
Weight matrix 'W' is initialized by Equation;
$W_{ii} = exp(-a\, e_i^2)$
Initialize the median value to 1.
Output**:** Reconstructed image X.
Loop **:** Compute the value of k = 1, 2 …k;
Calculate $\alpha^{(k+1)}$ with Equation;
$\alpha^{(k+1)} = (\Phi^T W \Phi + V^{k+1})^{-1} (\Phi^T W Y - \Phi^T W)+\mu$
Calculate $x^{(k)} = \Phi \alpha^{(k)}$ with updating the nonlocal coding vector;
Calculate the residue with equation
$e^{(k)} = Y-x^{(k)}$
Compute the weights of matrix 'W' with '$e^{(k)}$' using Equation;
$W_{ii} = exp(-a\, e_i^2)$
End **:** Denoised image is output,
obtained as $x = \Phi \alpha^{(k)}$.

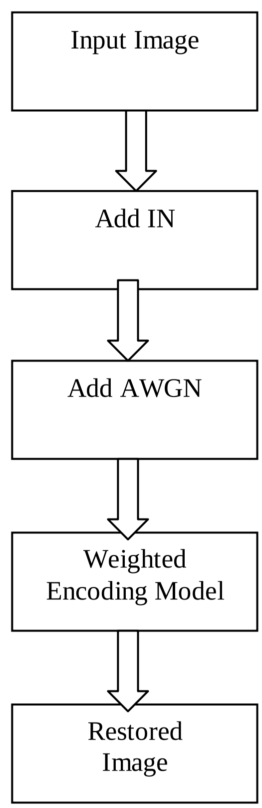

Fig. 3: Process flow of the Weighted Encoding Model

IV. RESULT AND ANALYSIS

In the paper there are two types of mixed noise: AWGN+SPIN and AWGN+RVIN+SPIN. here PSNR and FSIM(which are quality index) values are compared between WESNR algorithm and other state of art method.

Figure 4.1 -4.12 shows the snap shots of execution of WESNR algorithm. Fig 4.1-4.6 illustrate AWGN+SPIN removal by applying WESNR algorithm and Fig 4.7 -4.12 illustrate AWGN+SPIN+RVIN removal by applying WESNR algorithm.

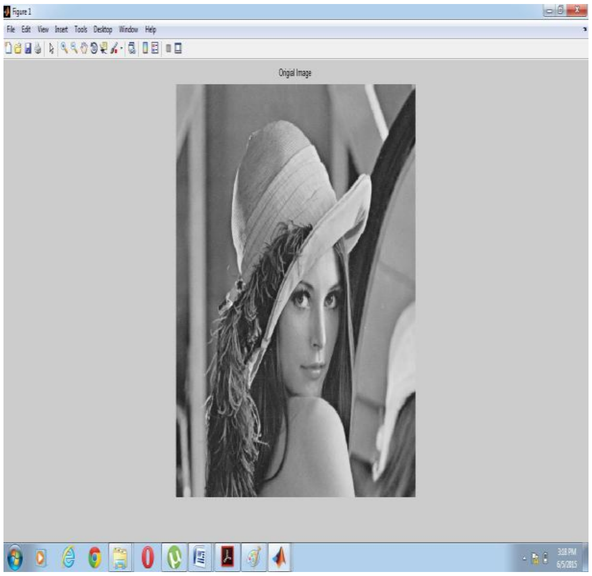

Figure 4.1: original image of Lena

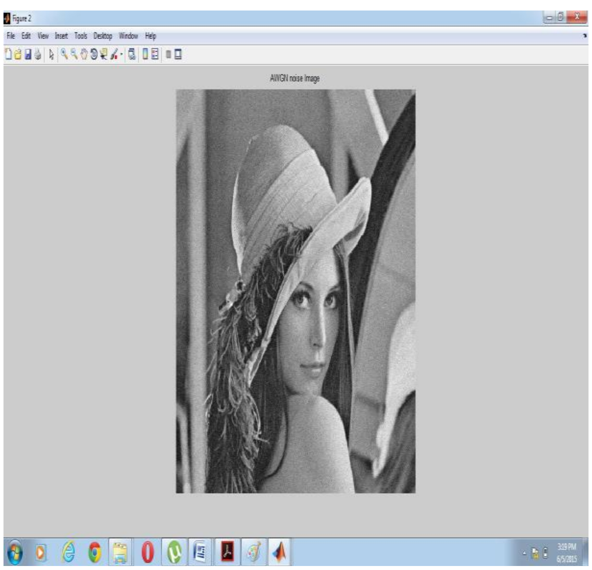

Figure 4.2: AWGN of Lena image

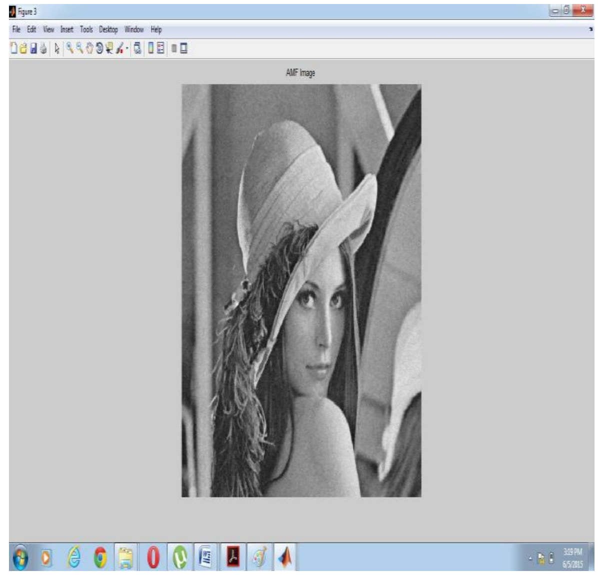

Figure 4.3: AMF of Lena image after AWGN

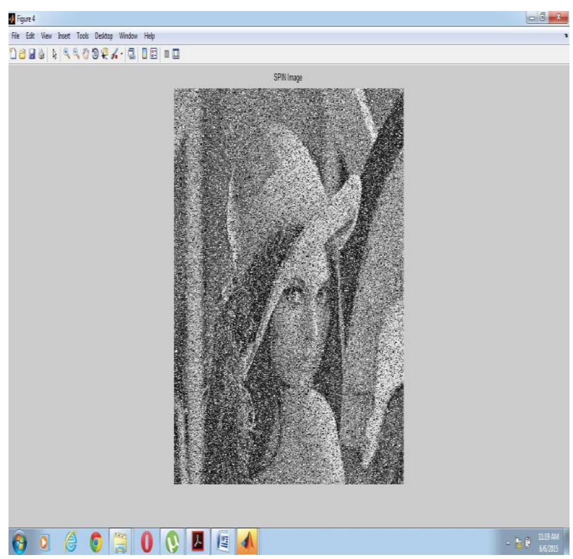

Figure 4.4: SPN of Lena image

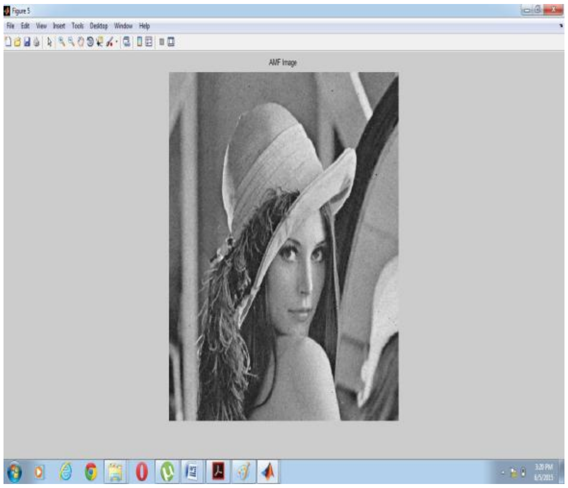

Figure 4.5: AMF of Lena image after SPN

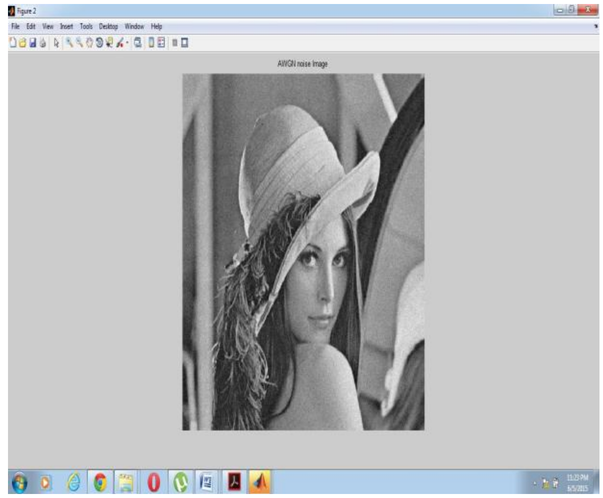

Figure 4.8: AWGN of Lena image

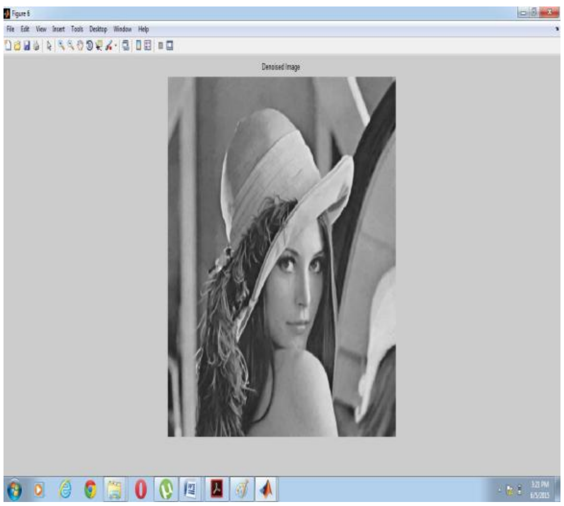

Figure 4.6: Denoised of Lena image

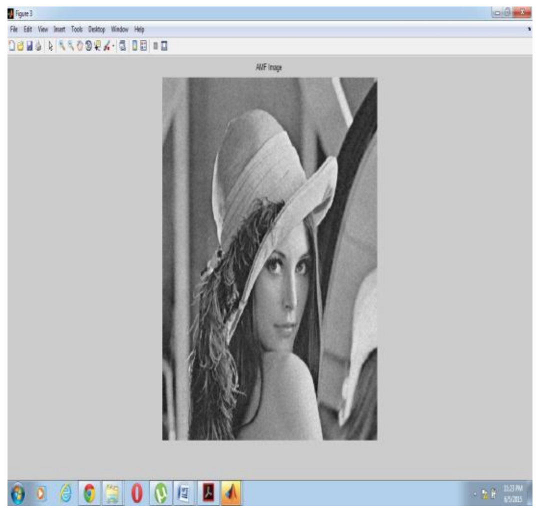

Figure 4.9: AMF of Lena after AWGN

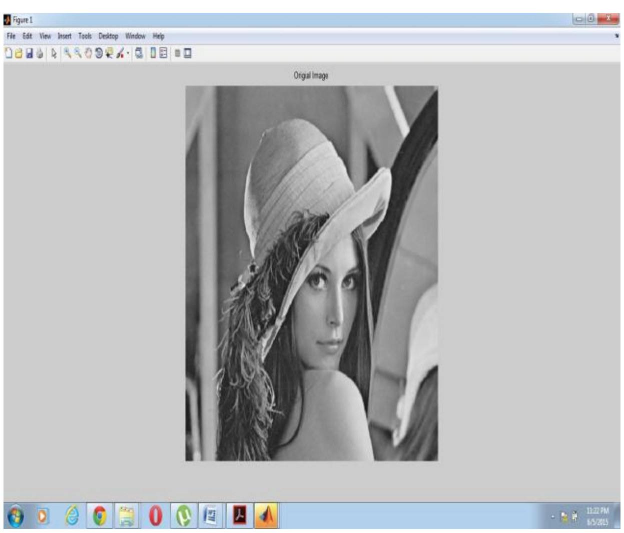

Figure 4.7: Original image of lena

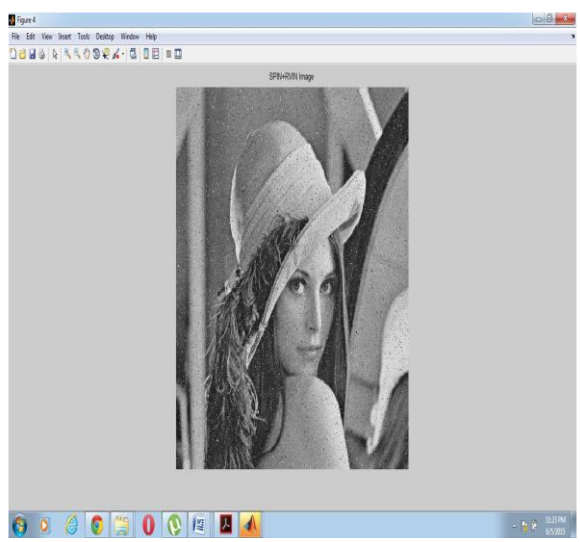

Figure 4.10: SPIN+RVIN of Lena image

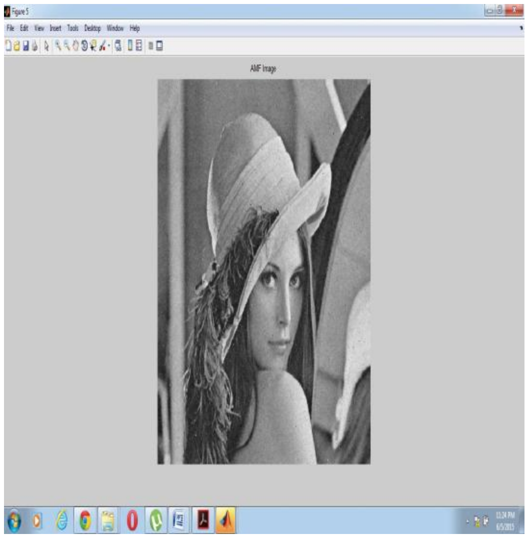

Figure 4.11: AMF of Lena image after SPIN+RVIN

Figure 4.12: De-noising image

Figure 4.1 -4.12 shows the snap shots of execution of WESNR algorithm. Fig 4.1-4.6 illustrate AWGN+SPIN removal by applying WESNR algorithm and Fig 4.7 -4.12 illustrate AWGN+SPIN+RVIN removal by applying WESNR algorithm.

CONCLUSION

In proposed WESNR algorithm deals with both mixed noise types of AWGN+SPIN and AWGN+SPIN+RVIN which is more powerful and also runs faster than the state of art method .it deals with both weighted encoding and sparse non-local regularization which suppress IN and AWGN respectively, both of the terms are necessarily importance and they work simultaneously to remove mixed noise. In this algorithm dictionary kept offline learned i.e.,it is fixed in whole algorithm.WESNR algoritm is simpler which is easily solved by the iteration re- weighting method.the results illstrates that this method is much better than the state of art method.

Figure 4.13 – 4.17 shows the denoising of colour image. The results obtained using Fuzzy filter technique ensures noise free and quality of the image as well.The main advantages of this fuzzy filter are the denoising capability of the destroyed color component differences.

PERFORMANCE MEASURE

The Peak Signal to Noise Ratio (PSNR) is the value of the noisy image with respect to that of the original image. The value of PSNR and MSE(Mean square Error)for the proposed method is found out experimentally. The PSNR and the Mean Square Error of the retrieved image can be calculated by using the equations :

$$\text{PSNR (Img, Org)} = \frac{10 \log_{10} \quad S^2}{\text{MSE (Img, Org)}}$$

$$\text{MSE(Img, Org)} = \frac{(\Sigma_{c=1}\Sigma_{i=1}\Sigma_{j=1}[\text{Org}(i,j,c) - \text{Img}(i, j,c)]^2}{3NM}$$

Where Org is the original image, Img is the filtered color image of size M. M, S is the maximum possible intensity value with m-bit integer values, S will be 2^m-1). The results of the calculations for the proposed method are given in Table I.

Table 1: Performance Measure

Filter	MSE(Mean Square Error)	PSNR (Peak Signal to Noise Ratio) in dB
Linear smoothing filter	265.1121	55.0237
Median filter	131.3515	62.0465
Weiner filter	39.2500	74.1258
WESNR filter	3.3282	98.8009

(a)Original image (b)Using linear filter (c)Using median filter (d) Using weiner filter (e) Using WESNR filter

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