DE-NOISING OF IMAGES CORRUPTED IN PRESENCE OF 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. 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.

This 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). This 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 effect.

Keywords: AWGN, IN, Mixed noise and weighted encoding, RVIN, SPIN, WESNR.

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 major difficulty in the branch of image processing. This operation aims at the maximum preservation of fine details, image edges and textures maintaining with respect to noised image in comparison with 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 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 this paper is to implement an effective method to remove the mixed noise, using combination of new Weighted Encoding and Sparse Nonlocal Regularization (WESNR) process.

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].

III. MATHEMATICAL MODEL

3.1 De-Noising Model

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

3.2. Parameter Setting

For good performance parameter setting step plays a major role, to obtain our WESNR role all parameter used in algorithm are fixed by the experience. the two parameter are used to compute the diagonal matrix V: λ and ε,we put λ as 0.0001 since to weaken the role of non-local regularization term which is manily used in algorithm to remove AWGN and also first loop is removing IN which is not accurate due to non-local regulization regularization which is not useful .in second loop,IN is reduced largely so non-local similar regularization becomes more accurate ,therefore λ becomes larger value to remove AWGN . It comes to conculsion that if standard deviation for AWGN removal is higher than 10 then we assign λ as 1 else 0.5 to supress AWGN in preserving image details.ε is assign as small value as 0.1.

3.3 Algorithm Steps:

1.Input: Generate dictionary 'Φ' over the noisy image *Y;*

Residue 'e' is initialized by

Equations;

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

2. Output: Reconstructed image X.

3. 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;

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

4. End : Denoised image is output,

obtained as $x = \Phi\ \alpha^{(k)}$.

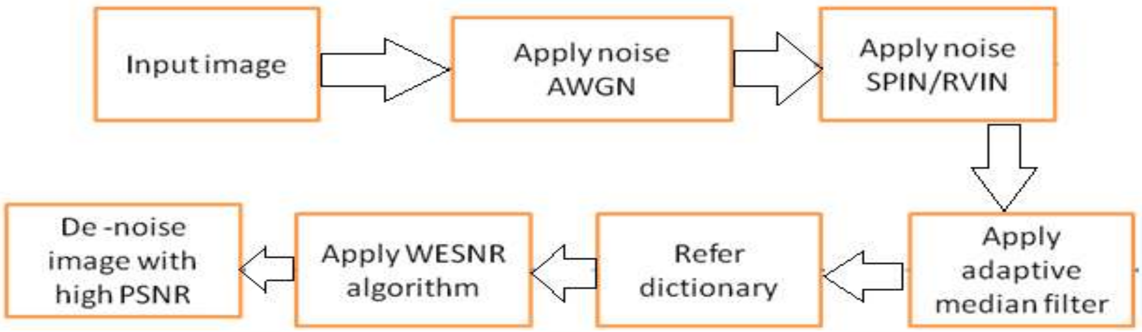


Fig: Block Diagram of the Algorithm.

IV. RESULT AND ANALYSIS

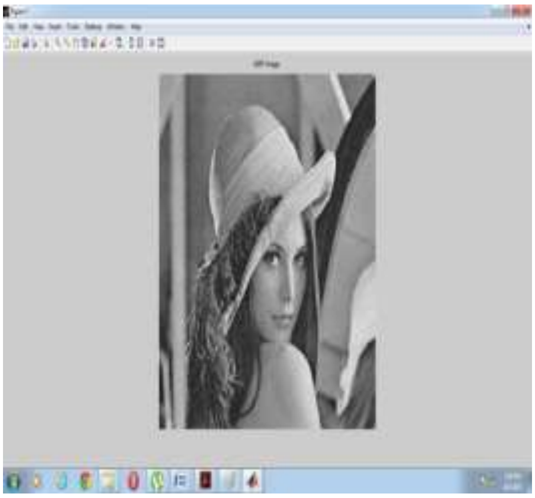
In this paper there are two types of mixed noise: AWGN+SPIN and AWGN+RVIN+SPIN. For AWGN+SPIN will be compared with state of art methods.

State of art methods source code are obtained from the original authors, here we are comparing PSNR and FSIM(which are quality index) values with WESNR algorithm and 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.

International Journal of Advanced Technology in Engineering and Science
Vol. No.4, Issue No. 05, May 2016
www.ijates.com
ijates
ISSN 2348 - 7550

Figure 4.1: Original image of Lena   Figure 4.2: AWGN of Lena image



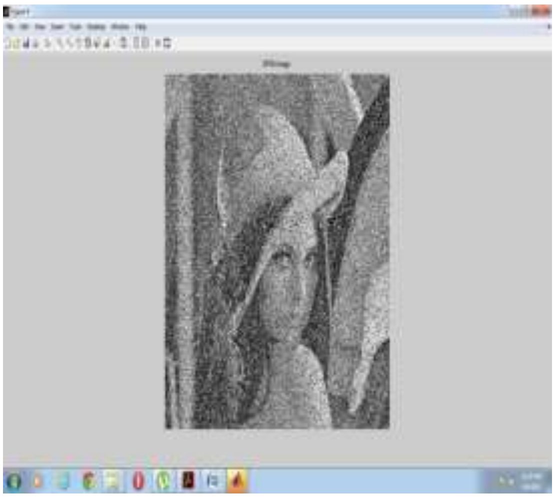
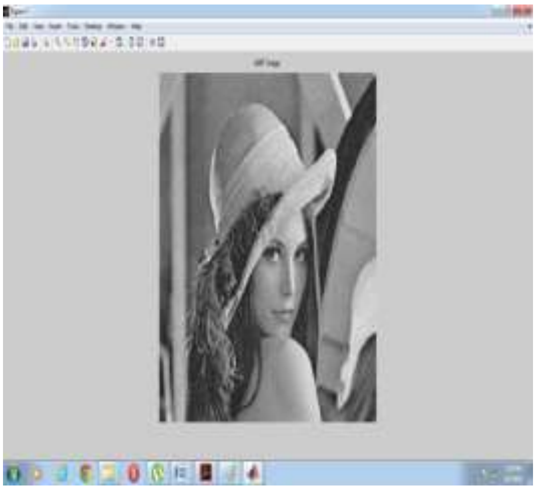


Figure 4.3: AMF of Lena image after AWGN Figure 4.4: SPN of Lena image



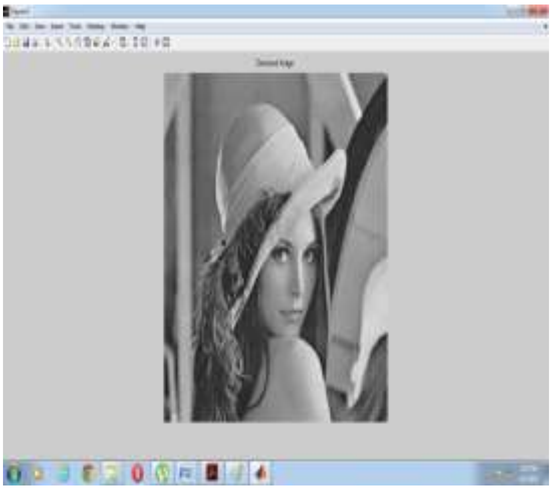


Figure 4.5: AMF of Lena image after SPN   Figure 4.6: Denoised of Lena image

International Journal of Advanced Technology in Engineering and Science
Vol. No.4, Issue No. 05, May 2016
www.ijates.com
ijates
ISSN 2348 - 7550

Figure 4.7: Original image of lena **Figure 4.8: AWGN of Lena image**

Figure 4.9: AMF of Lena after AWGN **Figure 4.10: SPIN+RVIN of Lena image**

Figure 4.11:AMF of Lena image after SPIN+RVIN **Figure 4.12: De-noising image**

V.CONCLUSION AND FUTURE SCOPE

5.1 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.

5.2 Future Scope

In future by implementing this algorithm we can implement the colour image and also we can use for de-blurring of an image.

VI. ACKNOWLEDGMENT

I am deeply indebted to my guide, Assistant Professor Sangam Borkar for allowing me to carry out this project under his supervision. He has given me confidence to take up this project and is a pillar of support that I have banked in times of difficulty.

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