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Denoising of Images Corrupted By Mixed Noise Using Improved WESNR Method

Rooby M[1], Harish Binu K P[2]

[1]PG scholar, MEA Engineering College, Perinthalmanna, Calicut University, India

[2]Assistant Professor, MEA Engineering College, Perinthalmanna, Calicut University, India

Abstract: ***Digital images play very consequential role in modern day to day life applications as well as in the areas of researches and technologies. Effectively remove noise from an image while keeping its features intact is a fundamental problem of image processing. Image denoising is the process or technique of removing noise from images. One typical kind of mixed noise is Impulse Noise (IN) coupled with Additive White Gaussian Noise (AWGN). This work introduces a method of denoising using Decision Based (DB) Weighted Encoding with Sparse Nonlocal Regularization (WESNR) to remove mixed IN and AWGN. Experimental results shown in terms of both visual quality as well as in quantitative measures that proposed method achieves leading mixed noise removal performance.***

Keywords: Image Denoising, Impulse Noise, Additive White Gaussian Noise, Peak Signal to Noise Ratio, Decision Based Filter.

1. Introduction

Images could be contaminated by noise during image acquisition, transmission due to malfunctioning pixel elements in the camera sensors, errors in transmission, faulty locations in memory, and timing errors in analog-to-digital conversions. It is very common that images are contaminated by noises due to several unavoidable reasons. Poor image sensors, unperfected instruments, problems and errors with data acquisition process, transmission errors and interfering natural and common phenomena are its main sources. Therefore, it is necessary to remove noises present in the images.

Remove noise from an image while keeping its features intact is an important problem of image processing. The nature of the problem depends on the type of noise added to the image [1]. There are several types of noises. Various types of noises have their own characteristics and are inherent in images in different ways and techniques. Gaussian noise, Speckle noise, Impulse noise, Amplifier noise, Salt & Pepper Noise (SPN), Poisson noise, Random valued noise are most widely occurred types of noise. Mixture or combination of these noises is also occurring. Mixed noise is the worst among them.

Image denoising is a process in image processing in which involves the manipulation of image data to produce a visually and theoretically high quality image. Simply, denoising or noise reduction is the process of removing noise from image. The working mechanism of denoising in image is shown in Figure 1 below. Various techniques of image processing such as edge enhancement, edge detection, object recognition, image segmentation, tracking of object etc. do not perform well in noisy environment. There has been rapid progress in denoising in the fields of image processing. Related works on image denoising [1]-[5] have been reviewed and observed that the WESNR method is efficient and effective.

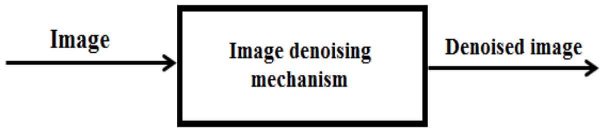

Figure 1. Working of denoising mechanism

2. Background

Image denoising is often used in the field of photography or publishing where an image may degraded but needs to be improved before it can be printed. Therefore, image restoration is applied as a pre-processing step before applying any of these above mentioned steps. Due to the thermal movement of electrons in camera sensors and circuits, AWGN is often introduced. IN occur by faulty memory locations in hardware, or bit errors in transmission, malfunctioning pixels in camera sensors. To smooth out the noisy pixels while keeping edge features so that there is no adverse effect of noise removal technique on the image is the purpose of various image restoration methods. Several techniques are proposed for image denoising and each technique has its own advantages and disadvantages. Some improper methods may badly affect the result of denoising and sometimes it change the content of image, produce artifacts, blurs the image, making the denoised images look unnatural. Therefore, selection of good denoising method is an important task in image processing as well as in day to day applications.

3. Literature Survey

In this survey, different relevant methods used for mixed noise denoising have been reviewed.

R. Garnett, T. Huegerich, C. Chui, and W. He [1] proposed a methodology which intends to remove the noise present in the images by using the impulse noise removal mechanism. In this mechanism noisy features are removed based on the most similar neighbors present in the images. In this work, a filter is designed based on the additive Gaussian noise. The trilateral filter is used to remove any kind of noises present in the images. This method incorporates the Rank-Order Absolute Difference (ROAD) statistic into the bilateral filtering by adding a third component to the weighting function. The new nonlinear filter is called the trilateral filter, whose weighting function contains spatial, radiometric, and impulsive components. The radiometric component combined with the spatial component smooth's away Gaussian noise and smaller impulse noise, while the impulsive component removes larger impulses. A switch based on the ROAD statistic is adopted to adjust weight distribution between the radiometric and impulsive components.

Bo Xiong and Zhouping Yin [2] introduced a novel framework for denoising approach through which the qualified image can be retrieved. This framework intends to filter the universal noises from the images based on the Non-Local Means filter. This work will be carried out in two levels. First is to calculate the Robust Outlyingness Ratio from the pixels present in the noised images. Second to implement the different types of decision rules in order to filter the noises present in the images. The proposed approach can be adapted to various models such as salt-and-pepper impulse noise, random-valued impulse noise, and mixed noise by modifying some parameters in the algorithm. This method is also known as ROR-NLM.

K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian [3] proposed a new methodology for restoring the images by using 3D transform domain collaborative filtering. In order to handle the 3D images effectively in this work collaborative filtering is introduced. The result is a 3-D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, the collaborative filtering reveals even the finest details shared by grouped blocks and, at the same time, it preserves the essential unique features of each individual block. Given a group of n fragments, the collaborative filtering of the group produces n estimates, one for each of the grouped fragments. In general, these estimates can be different. The term "collaborative" is taken literally, in the sense that each grouped fragment collaborates for the filtering of all others, and vice versa. The filtered blocks are then returned to their original positions. Because these blocks are overlapping, for each pixel, it obtains many different estimates which need to be combined. Aggregation is a particular averaging procedure which is exploited to take advantage of this redundancy.

P. Rodríguez, R. Rojas, and B. Wohlberg [4] introduced another novel mechanism for eliminating noises present in the images and restoring the original images with comparatively good quality. In this method, they introduced a novel mechanism called the total variation level through which it can eliminate noises accurately. Several Total Variation (TV) regularization methods have recently been proposed to address denoising under mixed Gaussian and impulse noise. While achieving high-quality denoising results, these new methods are based on complicated cost functions that are difficult to optimize, which negatively affects their computational performance. In this work, new method is introduced a simple cost functional consisting of a TV regularization term and data fidelity terms, for Gaussian and IN respectively, with local regularization parameters selected by an IN detector.

J. Jiang, L. Zhang, and J. Yang [5] also proposed a simple yet effective method, namely Weighted Encoding with Sparse Nonlocal Regularization (WESNR), for mixed noise removal. The role of weighted encoding is to suppress IN and the role of sparse nonlocal regularization is to suppress AWGN [5]. In WESNR, the weights $\boldsymbol{W}$ are introduced in the data fidelity term, and they are adaptively updated in the iteration process [5]. $\boldsymbol{W}$ are with real values, and the pixels corrupted by IN will be assigned small weights to reduce their effect on the encoding of $\boldsymbol{y}$ over the dictionary $\boldsymbol{\Phi}$ so that clean images can be reconstructed [5]. Once the dictionary $\boldsymbol{\Phi}$ is adaptively determined for a given patch, the proposed WESNR model can be solved by iteratively updating $\boldsymbol{W}$ and $\boldsymbol{\alpha}$. The updating of $\boldsymbol{W}$ depends on the coding residual $\boldsymbol{e}$. First apply Adaptive Filters (AF) [6] to the noisy image to obtain initialized image. In this algorithm, a set of orthogonal PCA dictionaries are pre learned from some high quality images, and one local PCA dictionary is adaptively selected to process a given image patch.

3.1 Observations and Analysis

Reconstructed images with higher Peak Signal to Noise Ratio (PSNR) and low Mean Square Error (MSE) values are judged better. The performance comparison of different methods based on running time, PSNR and MSE is shown as a Table 1. Comparison of Different Methods.

ROAD will produce false values when half of the pixels in the processing window are corrupted by noise. Trilateral Filter (TF) is basically a type of local non-linear filtering approach and thus simple architecture, but the denoised image quality is very poor. 3D transform domain collaborative filtering approach is somewhat complex architecture and average performance. Total Variation Regularization method performs well but with much computational complexity. WESNR mainly focuses on mixed noise denoising which does not have explicit impulse pixel detection step and simultaneously process AWGN and IN. WESNR method shows very powerful mixed noise removal performance than TF, ROR-NLM, 3D Transform Domain Collaborative Filtering and TV method. These methods consider Salt and Pepper Impulse Noise & Random Valued Impulse noise separately with AWGN.

Table 1: Comparison of Different Methods

Method	*Running Time*	*PSNR*	*MSE*
Trilateral Filter	Very Low	Very Low	Very High
ROR NLM	Very High	Low	Average
3D Transform Domain Collaborative Filtering	High	Average	Average
Total Variation Regularization	Average	Average	Average
WESNR	Very Low	High	Very Low

4. Problem Statement

However, when applied to image with mixed noise, it often produces visually unpleasant artifacts. Two types of IN are Salt and Pepper Impulse Noise (SPIN) and Random Valued Impulse Noise (RVIN). In WESNR denoising method if the noise contains AWGN & Salt and pepper Impulse Noise (SPIN) the initialized image is obtained using Adaptive Median Filter and if it also contains Random Valued Impulse noise (RVIN) the initialized image is obtained using Adaptive Center Weighted Median Filter [6], [7], [8]. The time complexity also somewhat high and minor artifacts remain. One natural question is that can we develop a mixed noise removal method which does not perform IN removal separately but conducts the two tasks in a unified framework?

5. Proposed Work

The paper is organized as follow: In Section 5.1 begins the discussion with an Initialized image using Decision Based Filter (DBF) [9], Section 5.2 discusses Weighted Encoding with Sparse Nonlocal Regularization method, and Section 5.3 explains methods for evaluation of proposed method. In Section 6 Results and evaluation of the accuracy of the proposed work and the base work using different measurements. In Section 7 Conclusion and Future work of this paper. The working architecture of the method is explained in Figure 2.

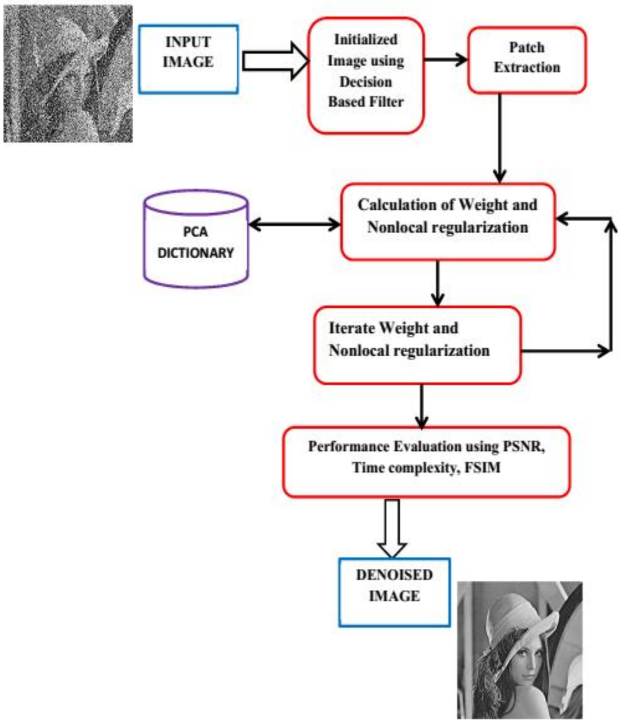

Figure 2: Working of proposed improved WESNR

5.1 Initialized Image using Decision Based Filter (DBF)

Two Adaptive Filters used in [5] is replaced using this single Decision Based Filter. The impulse noise pixels can take the maximum and minimum values in the dynamic range (0, 255). If the value of the pixel processed is within the range, then it is an uncorrupted pixel and left unchanged. If the value does not lie within this range, then it is a noisy pixel and is replaced by the median value of the window or by its neighborhood values. If the noise density is high, there is a possibility that the median value is also a noise value. In the latter case, the pixel processed is replaced by the previously processed adjacent neighborhood pixel value in place of the median value. The Decision Based Filter working is as follows.

1. A 2-D window "S_{XY}" of size 3X3 is selected. Assume the pixel to be processed is P(X,Y).
2. The pixel values inside the window are sorted, and P_{min}, P_{max} , and P_{med} are determined as follows.
   a) The rows of the window are arranged in ascending order.
   b) The columns of the window are arranged in ascending order.
   c) The right diagonal of the window is now arranged in ascending order.

Now the first element of the window is the minimum value , the last element of window is the maximum value , and the middle element of the window is the median value .

3. Case 1) The P(X,Y) is an uncorrupted pixel if P_{min}< P(X,Y) < P_{max} , P_{min} > 0 and P_{max} < 255 ; the pixel being processed is left unchanged. Otherwise, P(X,Y) is a corrupted pixel.

   Case 2) If P(X,Y) is a corrupted pixel, it is replaced by its median value if P_{min}< P_{med} < P_{max} and 0< P_{med} <255. Case 3) If P_{min} < P_{med} < P_{max} is not satisfied or 255 < P_{med} = 0 , then is a noisy pixel. In this case, the P(X,Y) is replaced by the value of neighborhood pixel value.

Steps 1 to 3 are repeated until the processing completed for the entire image.

5.2 Weighted Encoding with Sparse Nonlocal Regularization

Denote by $\boldsymbol{x} \in R^N$ an image. Let $\boldsymbol{x_i} = \boldsymbol{R_i x} \in R^n$ be the stretched vector of an image patch of size $\sqrt{n} \times \sqrt{n}$, where $\boldsymbol{R_i}$ is the matrix operator extracting patch $\boldsymbol{x_i}$ from $\boldsymbol{x}$ at location i. Based on the sparse representation theory, find an over complete dictionary $\boldsymbol{\Phi} = [\varphi 1; \varphi 2; . . . ; \varphi n] \in Rn \times m$ to sparsely code $\boldsymbol{x_i}$, where $\boldsymbol{\varphi}\, j \in R^n$ is the j *th* atom of $\boldsymbol{\Phi}$. The representation of $\boldsymbol{x_i}$ over dictionary $\boldsymbol{\Phi}$ can be written as

$$\boldsymbol{x_i} = \boldsymbol{\Phi \alpha_i} \qquad (1)$$

where $\boldsymbol{\alpha_i}$ is a sparse coding vector with only a few non-zero entries. The least square solution of $\boldsymbol{x}$ can be obtained as

$$\boldsymbol{x} = \boldsymbol{\Phi \alpha} \qquad (2)$$

where $\boldsymbol{\alpha}$ is the set of all coding vectors $\boldsymbol{\alpha_i}$. In image denoising, the observation of $\boldsymbol{x}$ is noise-corrupted, and we can only encode the noisy observation $\boldsymbol{y}$ over the dictionary $\boldsymbol{\Phi}$ [10] to obtain the desired $\boldsymbol{\alpha}$.

The initialized image is obtained using DBF. In order to make the weighted encoding stable and easy to control, we set $W_{ii} \in [0, 1]$. One simple and appropriate choice of W_{ii} is

$$Wii = \exp(-aei2) \quad (3)$$

where a is a positive constant to control the decreasing rate of Wii w.r.t. ei . With Eq. (4), the pixels corrupted by IN will be adaptively assigned with lower weights to reduce their impact in the process of encoding. Let $\boldsymbol{V}$ be a diagonal matrix. We first initialize it as an identity matrix, and then in the $(k+1)th$ iteration, each element of $\boldsymbol{V}$ is updated as

$$V_{ii}^{(k+1)} = \lambda/((\alpha i(k) - \mu\ i)2 + \varepsilon 2)1/2 \quad (4)$$

where ε is a scalar and $\alpha(k)\ i$ is the $i\ th$ element of coding vector $\boldsymbol{\alpha}$ in the kth iteration. Then we update $\boldsymbol{\alpha}$ as

$$\boldsymbol{\alpha}\hat{}(k+1) = (\boldsymbol{\Phi T W \Phi} + \boldsymbol{V}(k+1))-1(\boldsymbol{\Phi T W y} - \boldsymbol{\Phi T W \Phi \mu})+\boldsymbol{\mu} \quad (5)$$

By iteratively updating $\boldsymbol{V}$ and $\boldsymbol{\alpha}$, the desired $\boldsymbol{\alpha}$ can be efficiently obtained.

Because of the weighting matrix $\boldsymbol{W}$, the IN pixels in the image can be well identified and their effect is suppressed in the encoding of $\boldsymbol{y}$. As a result, both IN and AWGN will be gradually removed in the iteration. The working architecture of the method is explained in Figure 2.

5.3 Methods for Evaluation of Proposed Method

Parametric Description: The performance parameters are most consequential criteria to justify results in image processing through evaluation [2]. The most paramount parameters considered in image processing are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

Peak Signal to Noise Ratio (PSNR) analysis uses a mathematical equation model to measure an objective difference between two images. It estimates the quality of a reconstructed image with respect to an original image. Denoised images with higher PSNR value are judged best [2]. PSNR is most easily defined via Mean Squared Error (MSE). MSE is the average squared difference between a reference image (original image) and distorted image (restored image). It is computed pixel by pixel by adding up the squared differences of all the pixels and dividing by the total pixel count. The denoised image with lower MSE shows better result. The PSNR [9], FSIM [11] and CPU computation time in seconds are calculated for the PA, and a comparison of performance is shown.

6. Result

All the algorithms are run under the Matlab R2014a programming environment on a PC equipped with 2.40 GHZ CPU and 3 GB RAM memory. The reconstruction algorithm has been evaluated in regards of reconstruction time and visual accuracy.

7. Reconstruction Time

Time measurements have been taken to evaluate reconstruction time for different noise density of WESNR and improved WESNR. The outputs of different methods with respect to running time in seconds of Lena image is shown in Figure 3 at different noise levels.

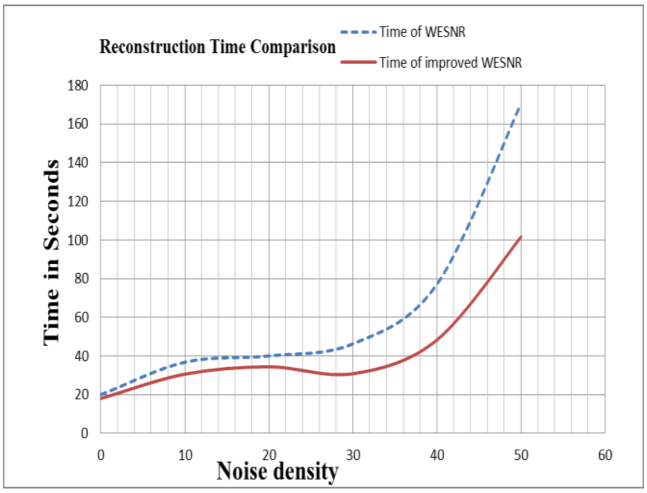

Figure 3: Running time in seconds of WESNR and improved WESNR

- **Quantitative Based Performance**

The accuracy of the proposed work has been evaluated by measuring PSNR value, FSIM [11] value of both WESNR method as well as proposed improved WESNR method. Figure 4 and Figure 5 shows the clear graph of performance based on PSNR and FSIM of different methods. The performance measurement based upon different noise densities.

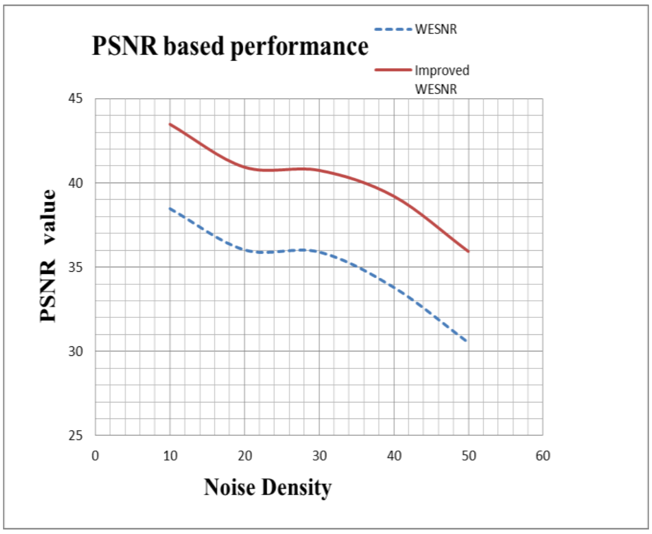

Figure 4: PSNR based performance of WESNR and improved WESNR

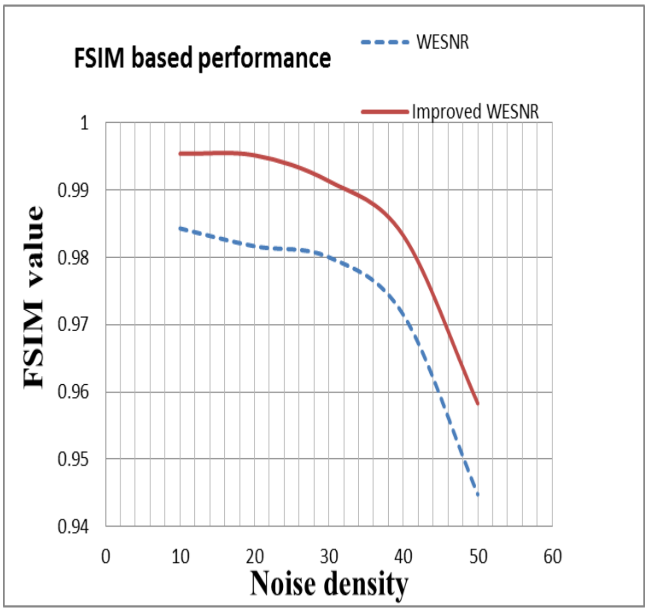

Figure 5: FSIM based performance of WESNR and improved WESNR

- **Visual Accuracy**

Conduct experiments on more than 50 Standard image processing images which are commonly used test images such as Lena, F16, Boat, Couple, Fingerprint, Hill, Man, Peppers, house, Camera Man, Mandrill etc. The outputs of different methods with different images with different types of noises are shown in Figure 6, Figure 7 and Figure 8 at different noise levels.

Figure 6: Denoising results of different methods on standard Lena image (a) Original Lena image (b) Image corrupted by mixed AWGN + SPIN at 50 % noise (c) Denoising result of WESNR (d)Denoising result of improved WESNR

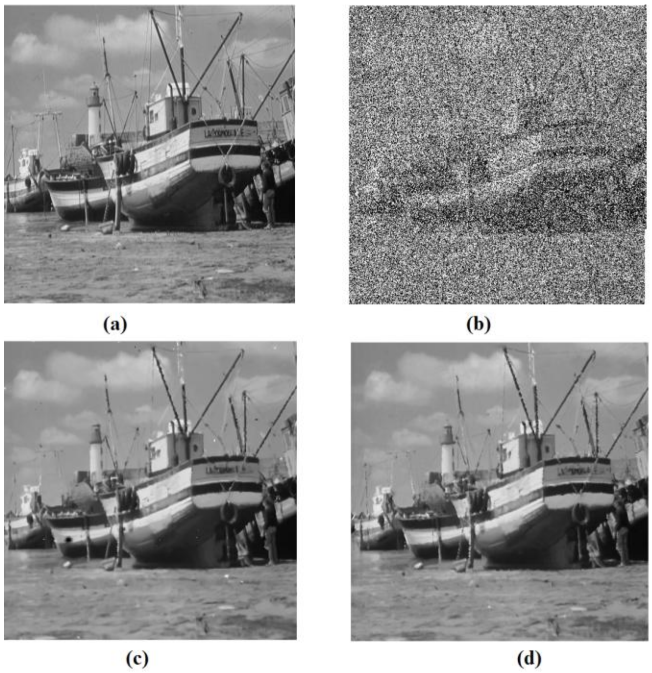

Figure 7: Denoising results of different methods on standard Boat image
(a) Original Boat image (b) Image corrupted by mixed AWGN + SPIN at 20 % noise (c) Denoising result of WESNR (d) Denoising result of improved WESNR

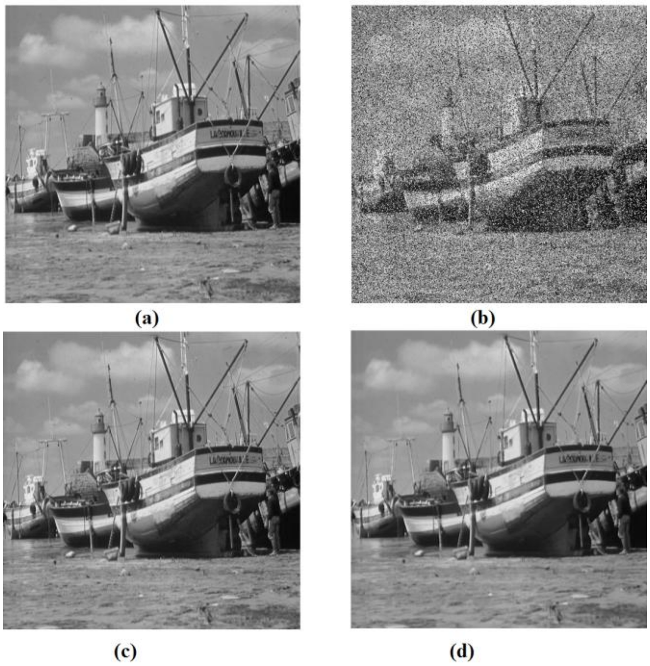

Figure 8: Denoising results of different methods on standard Boat image
(a) Original Boat image (b) Image corrupted by mixed AWGN + SPIN + RVIN at 20 % noise (c) Denoising result of WESNR (d) Denoising result of improved WESNR

Finally, let us compare the quantitative based performance such as PSNR, Running time, FSIM of above shown Boat image in Figure 8 with the given details is plotted as graph at WESNR and improved WESNR is shown below in Figure 9, Figure 10 and Figure 11 respectively.

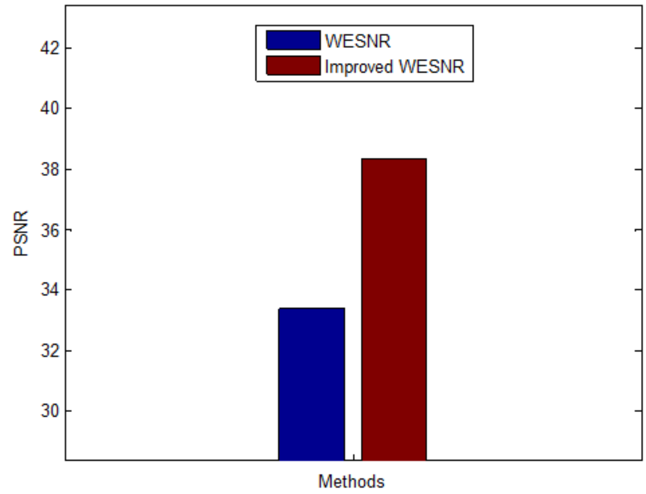

Figure 9: PSNR based performance of WESNR and improved WESNR at mixed AWGN + SPIN + RVIN at 20 % noise

All the algorithms are run under the Matlab R2014a programming environment. From the graphs it's clear that the proposed improved WESNR method exhibits higher PSNR value, lower running time and better FSIM value.

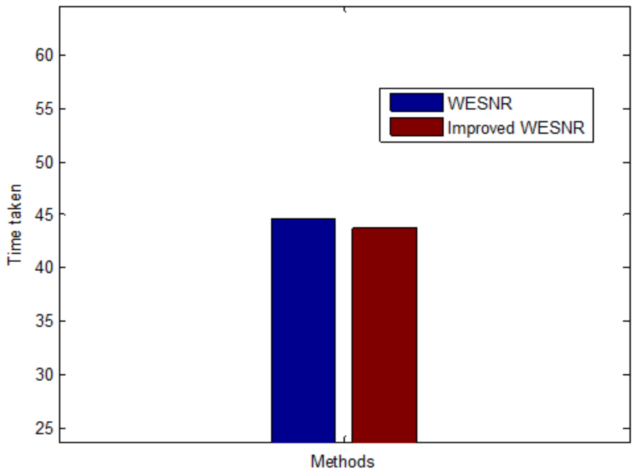

Figure 10: Running time in seconds of WESNR and improved WESNR at mixed AWGN + SPIN + RVIN at 20 % noise

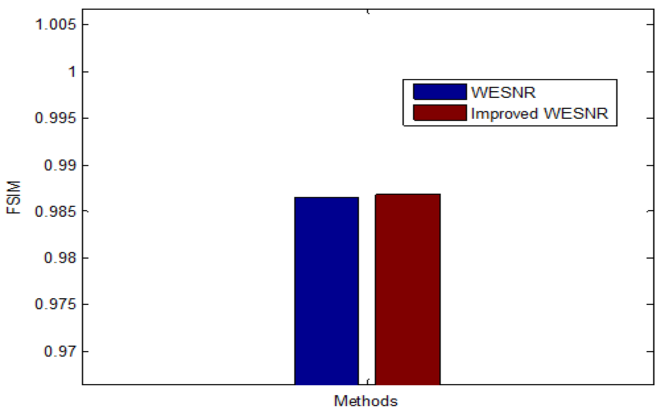

Figure 11: FSIM based performance of WESNR and improved WESNR at mixed AWGN + SPIN + RVIN at 20 % noise

8. Conclusion and Future Work

The distribution of mixed AWGN and IN is much more irregular than Gaussian noise alone, and often has a heavy tail. So to remove the difficulty, select weighted encoding to suppress IN and sparse nonlocal regularization to suppress AWGN. The proposed improved WESNR method used Decision Based Algorithm to obtain initialized image which reduce complexity, artifacts, blurring as well as increases efficiency. It can deal with mixed AWGN+SPIN noise and mixed AWGN+RVIN+SPIN noise. The superior denoising performance of proposed improved WESNR to other competing methods comes from both its weighted encoding based data fidelity term and sparse nonlocal regularization term. Results reveal that the proposed method exhibits better performance in terms of higher PSNR, FSIM and Running Time. Also provides more edge details, leading to better edge preservation, shows consistent and stable performance across a wide range of noise densities.

9. Acknowledgment

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Authors Profile

Rooby M received the B.Tech degree in Computer Science & Engineering from MEA Engineering College, Perinthalmanna, India under Calicut University in 2012. She is currently pursuing the M.Tech degree in Computer Science & Engineering from the same University and College. Her current research interest in image processing which mainly includes image denoising, medical image processing.

Harish Binu K P received the B.Tech degree in Computer Science & Engineering from NSS Engineering College, Palakkad, University of Calicut and M.tech degree in Computer Science from College of Engineering, Cochin university of Science and Technology. He is currently a Ass. Professor, under Calicut University at MEA Engineering College, Perinthalmanna. His research interest includes Image Processing and Digital design.