ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

An Effective Approach for Mixed Noise Removal Using WESNR and Modified Discrete Curvelet Transform

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ABSTRACT

Imaged noising is an important and a challenging task in many fields such as medical, satellite and remote sensing etc., because removal of noise will increase the perceptual quality of an image. In spite of the great success of many denoising algorithms, they were unable to remove the mixed noise, which will be generated by a mixture of random impulse noise (RIN) and additive white Gaussian noise (AWGN) or salt and pepper plus AWGN. To address this problem, in this paper we propose a mixed noise removal method by using weighted encoding sparse non local regularization (WESNR) algorithm and modified discrete Curvelet transform (MD-CVT). These algorithms are developed to risen the texture structures while removing noise. Experimental results shown that the proposed method has given the superior performance to the existing algorithms in terms of quantitative measures such as peak signal to noise ratio (PSNR), featured similarity index (FSIM), mean square error (MSE) and visual quality.

INTRODUCTION

In many applications, while transmitting the images and/or acquiringan image from both digital cameras will be affected with few or more amount of the noise from a variety of sources. Further processing of these noisy images can be done only after removal of this random noise, because this type of noise elements will create some serious issues in practical applications such as satellite, bio-medical, computer vision, remote sensing, artistic work or marketing and also in many fields. Denoising an image is a primary problem in the applications of image processing. Estimating an original image from the corrupted or sparse image by preserving its edge, texture and structural details is very important.In order to remove the noise from images, prior knowledge about the noise distribution plays a vital role. Mainly, there are two types of noises like impulse noise (IN), additive white Gaussian noise (AWGN). Due to the electrons thermal motion in camera sensors and circuits [22], AWGN will be introduced. In general, when there is a very small change in original pixel value that is known as Gaussian noise. Histogram is a graphical representation of image, which plots a discrete graph of the distortion amount of the pixel values at which frequency it exists, and shows a normal distribution of noise.

IN is often introduced due to improper functioning of camera sensors, hardware impairment memory locations or bit errors in transmission [23].Median filters [1] have been used dominantly to remove IN. Many improvements have been done in median filters to enhance the performance and to preserve the local structures [2-10], which includes weighted median filter (WMF) [3], multistate median filter (MMF) [4]

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International Journal & Magazine of Engineering, Technology, Management and Research
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and center weighted median filter (CWMF) [3]. All of them do not recognize that the present pixel is noisy or not and they tend to over smooth the denoised image. Hence, based on this concept several filters have been proposed in the literature such as switching median filter (SMF) [5], adaptive median filter (AMF) [6], tristate median filter (TMF) [7], adaptive CWMF [8], conditional signal AMF [9] and directional WMF [10] etc.

Bilateral filter (BF) [12] is a well-known nonlinear filter, which preserves the information about the edges. An extension for the BF is non local means (NLM) filtering algorithm [15]. BM3D approach has been proposed in [14] by combining the similar non local patches into a 3D cube and applying transform based shrinkage. Then after, LPG-PCA has been proposed in [16]. The work proposed in [13] initiates the dictionary learning from natural images to remove the AWGN and denoise the corrupted image using k- singular value decomposition (K-SVD). In [17], the author has proposed the use of both sparse representation and nonlocal self-similarity (NSS) regularization to remove the AWGN.

However, the mixture of both AWGN and IN increases the difficulties and makes much more complex to denoise the images. Very few methods have been developed in the literature to remove this mixed noise [22-36]. All the existing mixed noise removal methods are detection based schemes and mainly they involved in steps i.e., detection of noisy pixels and then noise removal. But, when the AWGN and IN are very strong then this two phase has become less effective in mixed noise removal from the corrupted images. Therefore, here we proposed a simple and effective approach which includes both weighted encoding with sparse nonlocal regularization (WESNR) and modified discrete Curvelet transform (MD-CVT) to improve the performance of mixed noise removal algorithms.

LITERATURE REVIEW

Many researchers have developed and published enough papers on removing or eliminating either IN or AWGN [12-20], however these methods were not supposed to remove the mixture of AWGN and IN. From the past decades, several algorithms have been proposed [22-36]to remove the mixed noise which occurs due to noise from multiple sources.

When some amount of original pixels will be replaced with the values of random noise and few pixels will remain unchanged is known as IN corrupted image. Generally, there are two types of IN that encountered in images are random valued impulse noise (RVIN) and salt and pepper impulse noise (SPIN). When an image shows that the bright region pixels as a dark pixels and dark region pixel values as a bright intensity values then an image may be corrupted with SPIN. Median filters [1] have been used dominantly to remove IN. However, median filters have been suffering from few shortcomings i.e., it does not preserve the edges information and destroys the local structures of image, which in results that the denoised images looks unnatural. When IN density is very high then this problem will become more serious. To solve this issues, many improvements have been done in median filters to enhance the performance and to preserve the local structures [2-10], which includes weighted median filter (WMF) [3], multistate median filter (MMF) [4] and center weighted median filter (CWMF) [3]. All of them do not recognize that the present pixel is noisy or not and they tend to over smooth the denoised image. Hence, one possible way is to detect or identify the IN corrupted pixels and leave the uncorrupted pixels as it is. Based on this concept several filters have been proposed in the literature such as switching median filter (SMF) [5], adaptive median filter (AMF) [6], tristate median filter (TMF) [7], adaptive CWMF [8], conditional signal AMF [9] and directional WMF [10] etc.

In image denoising literature, AWGN is a most widely studied noise model [12-20]. Conventional linear filtering schemes such as Gaussian filtering has been used to filer the noisy images those are corrupted by AWGN. But, it will over smooth the edges while removing the noise. To address this issue, nonlinear

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

filtering schemes have been developed in further years. Bilateral filter (BF) [12] is a well-known nonlinear filter, which preserves the information about the edges by estimating the denoised pixel as the neighboring pixels weighted average, but the weights are influenced by spatial and intensity similarity. An extension for the BF is non local means (NLM) filtering algorithm [15], in which the denoised pixel is estimated as the weighted average of the all its standardized pixels of an original image and these weights are influenced by the similarity between them. BM3D approach has been proposed in [14] by combining the similar non local patches into a 3D cube and applying transform based shrinkage.

Then after, by using these similar patches and grouping them into a matrix then applied principle component analysis (PCA) to denoise the AWGN image, which is known as LPG-PCA and it has been proposed in [16]. In recent years, an attractive attention has been made in image restoration and denoising algorithms by introducing dictionary learning and sparse representation schemes. The work proposed in [13] initiates the dictionary learning from natural images to remove the AWGN and denoise the corrupted image using k- singular value decomposition (K-SVD). In [17], the author has proposed the use of both sparse representation and nonlocal self-similarity (NSS) regularization to remove the AWGN.

However, the mixture of both AWGN and IN increases the difficulties and makes much more complex to denoise the images. Very few methods have been developed in the literature to remove this mixed noise [22-36]. Author in [24] proposed a mixed noise removal algorithm using median based signal dependent rank ordered mean (SDROM), but it produces bitter artifacts often. IN detection has been done by integrating the trilateral filter (TF) [27] with absolute difference of rank order (ROAD) statistics into the BF [12]. Switching BF [28] is a method of detection and replacement, which is also a modification to the BF. To decide the present pixel is a noisy or not, it computes the reference median. If the reference median and target pixel difference is large then the target pixel is a noise pixel and therefore mixed noise is eliminated by switching between AWGN and IN. A method in [31] is known as a two-phase method to restore the noisy images which were corrupted by mixed noise. Later on it has been improved and republished in [32] to increase the efficiency of denoised system. Xiao et al. proposed an $l_1 - l_0$ minimization method, it achieves good denoising performance but it has been suffering from higher computational complexity.

In [34], a total variation (TV) regularization method has been proposed to reduce the computational complexity by aiming in mixed noise removal with a cost functional consisting of regularization data fidelity terms l_2 and l_1. Dong et al. proposed a new frame work for denoising an image by introducing a new variable to comprise the outliers. Meanwhile, this term used as a regularizer by considering that the amount of damaged pixels by IN is very small. More recently, author in [36] proposed a method which incorporates both sparse coding and learning of dictionary, reconstructing an image, noise clustering and estimating the parameters into a four step framework by solving a minimization problem. All the existing mixed noise removal methods are detection based schemes and mainly they involved in steps i.e., detection of noisy pixels and then noise removal.

But, when the AWGN and IN are very strong then this two phase has become less effective in mixed noise removal from the corrupted images. Therefore, here we proposed a simple and effective approach which includes both weighted encoding with sparse nonlocal regularization (WESNR) and modified discrete Curvelet transform (MD-CVT) to improve the performance of mixed noise removal algorithms. This algorithm is more effective approach in denoising the both AWGN and IN with affecting the information of original image. There is no expressed detection of impulse noise in WESNRbut just we encode each corrupted patch over a pre-learned dictionary.

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PROPOSED FRAME WORK

Mixed noise model

Denote that an unknown clean image at its pixel positions is $x_{m,n}$, where m and n are the number of rows and number of columns. Consider that the noisy observationyand it is usually modeled as

$$y_{m,n} = x_{m,n} + v_{m,n} \qquad (1)$$

where $v_{m,n}$ is the additive white Gaussian noise (AWGN) with zero mean and standard deviation σ. Here, we assumed two types of mixed noise:

- AWGN+SPIN
- AWGN+RVIN+SPIN

The signal observation model for the first case can be expressed as:

$$y_{m,n} = \begin{cases} d_{\min} & with\ probability\ of\ s/2 \\ d_{max} & with\ probability\ of\ s/2 \\ x_{m,n} + v_{m,n} & with\ probability\ of\ 1-s \end{cases}$$

The observation model for the second case is as follows:

$$y_{m,n} = \begin{cases} d_{\min} & with\ probability\ of\ s/2 \\ d_{max} & with\ probability\ of\ s/2 \\ d_{m,n} & with\ probability\ of\ r(1-s) \\ x_{m,n} + v_{m,n} & with\ probability\ (1-r)(1-s) \end{cases}$$

Denoising model

Denote an image by $x \in R^P$. We let $x_m = R_m \in R^p$ as referenced in [13] be a patch size of stretched image vector, where R_m is the extracting patch x_m matrix operator at location m. As given in [37], we considered sparse representation theory to find the over-complete dictionary $\Phi = [\Phi_1; \Phi_2; \ldots; \Phi_p] \in R^{p,q}$ to sparsely code$x_m$where $\phi_j \in R^p$is the j^{th}atom of Φ.

The representation of $x_i$over the learning dictionary Φ can be expressed as follows:

$$x = \Phi\alpha \qquad (2)$$

Where α=set of all coding vectors α_i

The main objective of de-noising an image is to estimate the desired image $\hat{x}$ from y over the Φ. Then the encoding model can be done using

$$\hat{x} = arg \min_x \|y - x\|^2 + \lambda \cdot R(x) \qquad (3)$$

By substitute the eq. (2) in above equation, we can obtain the encoding model

$$\hat{x} = arg \min_\alpha \|y - \Phi\alpha\|_2^2 + \lambda \cdot R(\alpha) \qquad (4)$$

where R(α) denotes some regularization term that imposed on αand $\lambda$is a parameter of regularization. The specific form of R(x) depends on the employed image priors.

The coding vector which has been resolved is a maximum a posteriori (MAP) solution at certain regularization term [17,39] for AWGN model. However, the noise distribution in an images those are corrupted by mixed noise is far from Gaussian. Hence, the data fidelity term $\|y - \Phi\alpha\|_2^2$in eq. (4) will not lead to a MAP solution in removal of noise. From the fig 1, the data fitting residual distribution is much more irregular than Gaussian-like, then to characterize the residual of coding, one can use $l_2 - norm$ for handling mixed noise removal in a much easier way. This motivates us to use robust estimation methods [38,41 and 44] to weight the residual of data fitting so that it can be more regular.

Let,

$$e = [e_1; e_2; \ldots; e_P] = y - \Phi\alpha \qquad (5)$$

Where $e_i = (y - \Phi\alpha)(i)$. Instead of minimizing the $\|y - \Phi\alpha\|_2^2 = \sum_{i=1}^{P-1} {e_i}^2$, which actually assumes that e_i follows Gaussian distribution, , robust estimation technique [41,44] will be used to minimize the following loss:

$$min \sum_{i=1}^{P} f(e_i) \qquad (6)$$

The share of each residual to the whole loss will be controlled by the function *f*. IN general, it should have following properties: symmetric, nonnegative and monotonic. That is: 1. $f(e) \geq 0$ $f(0) = 0$; 2.$f(e_i) \geq f(e_j)$if $|e_i| \geq |e_j|$; 3.$f(e) = f(-e)$. To reduce the effect of mixed noise distribution, we can assign a proper weight to each residual, then the weighted residual is as follows:

$$e^w{}_i = {w_i}^{1/2} e_i \qquad (7)$$

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Residuals can be categorized into two parts:

i. Residuals found at AWGN corrupted pixels

ii. Residuals found at IN corrupted pixels

Generally, first category will be followed by Gaussian distribution i.e., the weights assigned to such pixels is close to 1. And to reduce the heavy tail of distribution we need to assign smaller weights to the IN pixels. Therefore, we adopted a novel function:

$$f(e_i) = \left({w_i}^{1/2} e_i\right)^2$$

And accordingly we have a new denoise model for removal of mixed noise:

$$\hat{x} = arg\min_{\alpha} \left\| W^{1/2}(y - \Phi\alpha) \right\|_2^2 + \lambda \cdot R(\alpha) \qquad (8)$$

W= diagonal matrix of weights with elements of diagonal. To made the eq. (8) more effective, we used some regularization terms based on the natural image priors. We have two priors that can be used widely for denoising of image:

1. Local sparsity
2. Non-local self-similarity (NSS)

Inspired by the work proposed in [17], two priors have been integrated into a single prior named as sparse non local regularization term. Then the eq. (8) can be rewritten as follows:

$$\hat{x} = arg\min_{\alpha} \left\| W^{1/2}(y - \Phi\alpha) \right\|_2^2 + \lambda \cdot R(\alpha)$$

Where $R(\alpha) = \sum_i \|\alpha_i - \mu_i\|_{l_p}$ (9)

$$\hat{x} = arg\min_{\alpha} \left\| W^{1/2}(y - \Phi\alpha) \right\|_2^2 + \lambda \cdot \sum_i \|\alpha_i - \mu_i\|_{l_p} \qquad (10)$$

Where p=1 or 2 refers to the l_p-norm

Finally, the proposed denoising model can be remodeled using the laplacian distribution and hence it could lead to MAP estimation as follows

$$\hat{x} = arg\min_{\alpha} \left\{ \left\| W^{1/2}(y - \Phi\alpha) \right\|_2^2 + \lambda \cdot \|\alpha - \mu\|_1 \right\} \qquad (11)$$

In the above eq. (11), the term W, which is a diagonal weight matrix can be selected as a choice of W_{ii} is

$$W_{ii} = exp\left(a e_i^2\right) \qquad (12)$$

Where, a=positive constant, which controls the decreasing rate of W_{ii} with respect to e_i

The proposed denoising model can be solved by updating the $W$and α, when the dictionary of learning will be determined adaptively for the given patch. As mentioned in eq. (12), updating the weights will be depended on residual of coding e,In the literature, AMF [6] has been used to detect SPIN widely. To make a fair comparison, first we apply AMF to the noisy image y, to get an image $x^{(0)}$, then coding residual can be initialized as:

$$e^{(0)} = y - x^{(0)} \qquad (13)$$

If we want to remove AWGN+SPIN+RVIN, AMF cannot be applied to y. In that case, coding residual can be initialized as

$$e^{(0)} = y - \mu_y \cdot 1 \qquad (14)$$

Where the mean value of all pixels in y is represented with $\mu_y$and 1 is a column vector that is whose elements are al 1.

MD-CVT Technique

The discrete Curvelet transform is an extension for the wavelets and rigelets.it can be defined as a continuous function $f(x_1, x_2)$makes use of a dyadic sequence of scales, and a bank of filters $(P_0 f, \Delta_1 f, \Delta_1 f, \ldots)$ with the property that the pass band filter $\Delta_s$is concentrated near the frequencies $[2^s, 2^{2s+2}]$. In the theory of wavelets, one uses decomposition into dyadic subbands$[2^s, 2^{2s+2}]$. In contrast, the subbands used in the discrete curvelet transform of continuous functions have the non-standard form$[2^s, 2^{2s+2}]$. The curvelet decomposition is the sequence of the following steps:

Subband Decomposition:

it decomposes the object f into several subbands

$$f \longmapsto (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$$

Smooth Partitioning:

this can be used to windowed the sub bands into a “squares” of an appropriate scale (of side length $\sim 2^{-s}$)

$$\Delta_s f \mapsto (w_Q \Delta_s f)_{Q \in Q_s}$$

Renormalization:

it is used to renormalize each square as a unit scale

$$g_Q = (T_Q)^{-1}(w_Q \Delta_s f), Q \in Q_s$$

Ridgelet Analysis:

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
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Now, ridgelet is used to analyze each square.
In this definition, the two dyadic subbands $[2^s, 2^{2s+1}]$ and $[2^{2s+1}, 2^{2s+2}]$ are merged before applying the ridgelet transform.

Algorithm 1: Removal of Mixed noise by using WESNR and MD-CVT

Input: Learning dictionary Φ, noisy observation y;
Initialize e, by eq. (14) or (15) and then initialize W by eq. (12);
Output: Denoised image $\hat{x}$
Loop: Iterate on $k = 0,1, \ldots, K$'

1. Compute $\alpha^{(k)}$by eq. (13)
2. Compute$x^{(k)} = \Phi\alpha^{(k)}$
3. Update the non local mean of coding vector μ
4. Compute the residual:$e^{(k)} = y - x^{(k)}$
5. Weights calculation by eq. (12)

End

6. Now, apply the à trous algorithm with scales
7. Set$B = B_{min}$
8. For $j = 1,2,3, \ldots J$ do

a) Partition the subband w_j with a block sizeB_j and apply the digital ridgelet transform to each block
b) If $j modulo\ 2 = 1\ then B_{j+1} = 2B_j$
c) else $B_{j+1} = B_j$

Output denoised image$\hat{x}$

SIMULATION RESULTS

Experimental results have been done in MATLAB 2014a version with 4GB RAM and i3 processor. To verify the performance of the proposed image denoising model using the WESNR and MD-CVT algorithms with the existing denoising techniques such as AMF, NLM, we tested it with various images such as satellite, biometric, medical and more even natural images with different texture structures. All the test images are intensity or gray-scale images with the pixels ranging from 0 to 255. We first discuss the parameter setting in our algorithm, and then compare the performance of proposed and its region based variants. Finally, experiments are conducted to validate its performance in comparison with the state-of-the-art denoising algorithms.

Several parameters are used in our proposed algorithm and they all can be fixed easily with our experience. First, the parameter τ is the termination of iteration controlling. To balance the denoising results, we set it to 0.003. In eq. (12), the parameter that is used to control the weights decreasing rate w.r.t. e, this can be set it to 0.0008. fig1 shows that the mixed noise removal from the Lena512.tif, it displayed all the denoised images obtained by using conventional AMF, NCSR, WESNR and proposed WESNR+MD-CVT algorithms.

Fig1. (a) Original image, (b) AWGN (c) Mixed noise with sigma=5 and (d) AMF filtered image(e) WESNR method and denoised using proposed

We can observe that the visual quality of the proposed scheme is very good and much improved over the existing techniques.

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International Journal & Magazine of Engineering, Technology, Management and Research
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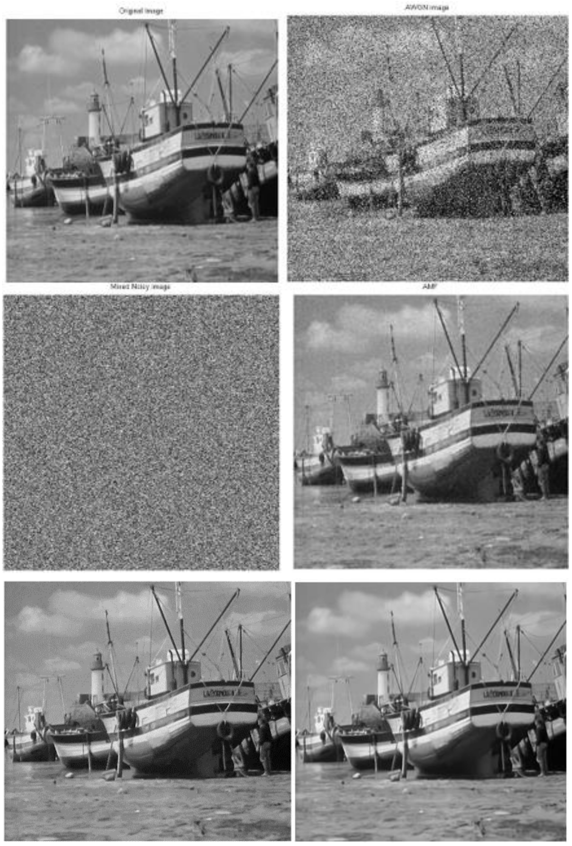

Fig2. original,AWGN noisy, mixed, AMF, WESNR and proposed denoised images

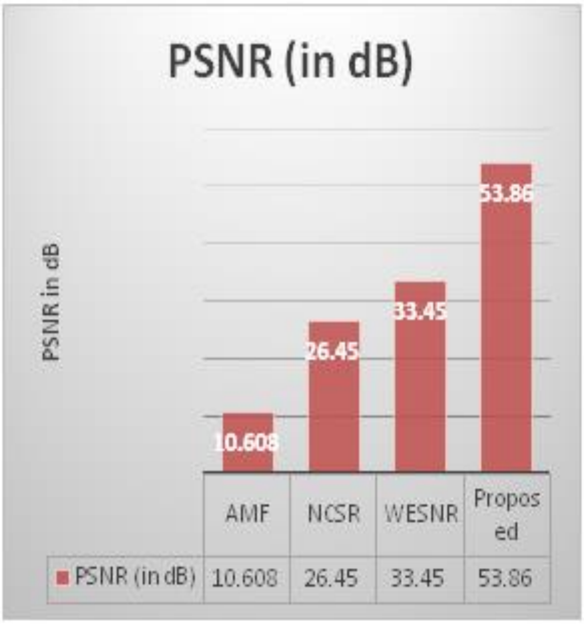

Fig.3 PSNR performance analysis of proposed and conventional models for Lena

Fig.4 FSIM comparison with proposed algorithm for Lena image

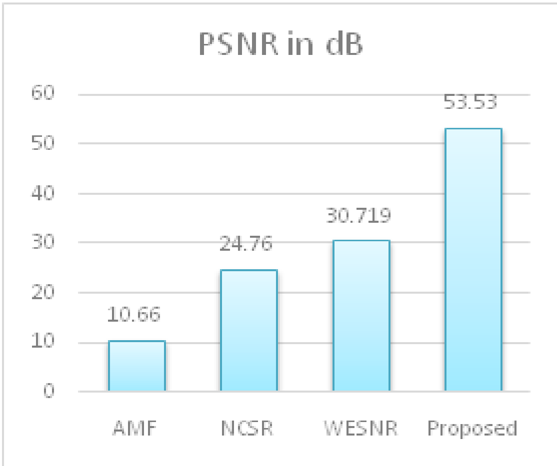

Fig5.PSNR comparison for boat image

Fig.6 FSIM comparison for boat image

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
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CONCLUSIONS

Here, we presented a novel denoising model for mixed noise using weighted encoding sparse non local regularization (WESNR) and modified discrete curvelet transform (MD-CVT). The mixed noise distributioni.e., Gaussian noise mixed up with random impulse noise is much more irregular over alone Gaussian noise also often has a heavy tail, and causes serious problems in image processing applications. To address this issue, we adopted a novel algorithm that removes the mixed noise more effectively and improves denoising system performance by increasing the PSNR and FSIM. Proposed algorithm achieves promising results in enhancing the mixed noisy image while removing AWGN and IN. The experimental results demonstrated the effectiveness of proposed algorithm. Most of the state-of-the-art denoising algorithms are based on the either local sparsity or nonlocal selfsimilarity priors of natural images. Unlike them, our proposed scheme used a kind of global prior, which is adaptively estimated from the given noisy image.

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