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A NEW INNOVATIVE APPROACH FOR MEDICAL IMAGE DENOISING USING GENETIC ALGORITHM AND THERSHOLDING

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Abstract— **The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Speckle noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. In this paper decompose the image using discrete wavelet and then applied genetic algorithm for feature selection and threshold for noise removal. The method used in this paper can efficiently remove a variety of noise while preserving the image information well. It is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR. The experimental results demonstrate its better performance compared with some existing methods.**

Keywords— ***Face Recognition, LTP, PCA, CMSC and Gradient Histogram***

I. INTRODUCTION

Image noise means unwanted signal. It is random variation of color information and brightness in images, and is usually an aspect of electronic noise. It is an undesirable by-product of image capture that adds spurious and extraneous information. Gaussian noise – One of the most occurring noise is Gaussian noise.Principal sources of Gaussian noise arise during acquisition e.g. sensor noise caused by poor illuminat ion and/or high temperature, and/or transmission e.g. electronic circuit noise. Gaussian noise represents statistical noise having probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. Image denoising refers to the recovery of a digital image that has been contaminated by Additive white Gaussian Noise (AWGN). AWGN is a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density (expressed as watts/ Hz of bandwidth) and a Gaussian distribution of amplitude. Salt-and-pepper noise–Fat-tail distributed or "impulsive" noise is sometimes called salt-and pepper noise.Any image having salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. In salt-and-pepper noise corresponding value for black pixels is 0 and for white pixels the corresponding value is 1. Shot noise–In the lighter parts of an image there is a dominant noise from an image sensor which istypically caused by statistical quantum fluctuations,that is, variation in the number of photons sensed at a given exposure level called photon shot noise. Quantization means the process of dividing, hence the noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise.In many applications, image denoising is used to produce good estimates of the original image from noisy observations. The restored image should contain less noise than the observations while still keep sharp transitions. Wavelet transform, due to its excellent localization property, has rapidly become an indispensable signal and image processing tool for a variety of applications, including compression and denoising. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. It involves three steps: a linear forward wavelet transform, nonlinear thresholding step and a linear inverse wavelet transform. An image is often corrupted by noise during its acquisition and transmission. Image denoising is used to remove the additive Gaussian noise while retaining important maximum possible image features. Wavelet analysis has been demonstrated to be one of the powerful methods for performing image noise reduction . The procedure for noise reduction is applied on the wavelet coefficients obtained after applying the wavelet transform to the im- age at different scales. The motivation for using the wavelet transform is that it is good for energy compaction since the small and large coefficients are more likely due to noise and important image features, respectively . The small coefficients can be thresholded without affecting the significant features of the image. In its most basic form, each coefficient is thresholded by comparing against a value, called threshold. If the coefficient is smaller than the threshold, it is set to zero; otherwise it is kept either as it is or modified. The inverse wavelet trans- form on the resultant image leads to reconstruction of the image. . A large number of different noise reduction methods have been proposed so far. Traditional denoising methods can be generalized into two main groups: spatial domain filtering and transform domain filtering. Spatial domain filtering methods have long been the mainstay of signal denoising and manipulate the noisy signal in a direct fashion. Conventional linear spatial filters like Gaussian filters try to suppress noise by smoothing the signal. While this works well in the situations where signal variation is low, such spatial filters result in undesirable blurring of the signal in situations where signal variation is high.

Curvelet and Wavelet Image Denoising [1]this paper describes the image denoising of Curvelet and Wavelet Image Denoising by using 4 different additive noises like Gaussian noise, Speckle noise, Poisson noise and Salt & Pepper noise and also by using 4 different threshold estimators like heursure, rigrsure, mini-maxi and squawolog for wavelet and curvelet transform both. It offer exact reconstruction, stability against perturbation, ease of implementation and low computational complexity. The curvelet reconstruction offering visual sharp image and in particular, higher quality recovery of edges and of faint linear and curvilinear features . Image Denoising Using Wavelet Thresholding [2] This paper proposes and explore different wavelets methods in digital image denoising. Using several wavelets threshold technique such as SURE Shrink, Visu Shrink, and Bayes Shrink in search for efficient image denoising method. This paper extend the existing technique and provide a comprehensive evaluation of the proposed method. Wiener filtering technique is the proposed method which was compared and analysed, while the performance of all the techniques were compared to ascertain the most efficient method. Image Denoising Techniques[3] This paper is to provide a review of some of those techniques that can be used in image processing (denoising). This paper outlines the brief description of noise, types of noise, image denoising and then the review of different techniques and their approaches to remove that noise . The aim of this paper is to provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs. Speckle Noise is a natural characteristic of medical ultrasound images. Speckle Noise reduces the ability of an observer to distinguish fine details in diagnostic testing. It also limits the effective implementation of image processing such as edge detection, segmentation and volume rendering in 3 D. Therefore; treatment methods of speckle noise were sought to improve the image quality and to increase the capacity of diagnostic medical ultrasound images. Such as median filters, Wiener and linear filters (Persona & Malik, SRAD ... ..).The method used in this work is 2-D translation invariant forward wavelet transform, it is used in image processing, including noise reduction applications in medical imaging[4]. Mohammad Ali says [5] A novel method for image denoising which relies on the DBNs' ability in feature representation. This work is based upon learning of the noise behavior. Generally, features which are extracted using DBNs are presented as the values of the last layer nodes. The nodes in the last layer of trained DBN are divided into two distinct groups of nodes. After detecting the nodes which are presenting the noise. A reduction of 65.9% in average mean square error (MSE) was achieved when the proposed method was used for the reconstruction of the noisy images. A novel self-learning based image decomposition framework. Based on the recent success of sparse representation, the proposed framework first learns an over-complete dictionary from the high spatial frequency parts of the input image for reconstruction purposes. This method perform unsupervised clustering on the observed dictionary atoms (and their corresponding reconstructed image versions) via affinity propagation, which allows us to identify image-dependent components with similar context information. The proposed and are able to automatically determine the undesirable patterns (e.g., rain streaks or Gaussian noise) from the derived image components directly from the input image, so that the task of single-image denoising can be addressed[6]. In Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising[7] Stacked sparse denoising autoencoders (SSDAs) have recently been shown to be successful at removing noise from corrupted images. However, like most denoising techniques, the SSDA is not robust to variation in noise types beyond what it has seen during training. This paper eliminate the need to determine the type of noise, let alone its statistics, at test time and even show that the system can be robust to noise not seen in the training set. It show that state-of-the-art denoising performance can be achieved with a single system on a variety of different noise types. Additionally, we demonstrate the efficacy of AMC-SSDA as a preprocessing (denoising) algorithm by achieving strong classification performance on corrupted MNIST digits. Contourlet Based Image Denoising[8] This paper proposed contour let based image denoising algorithm which can restore the original image corrupted by salt and pepper noise, Gaussian noise, Speckle noise and the poisson noise. The noisy image is decomposed into sub bands by applying contour let transform, and then a new thresholding function is used to identify and filter the noisy co efficient and take inverse transform to reconstruct the original image. This contourlet technique is computationally faster and gives better results compared to the existing wavelet technique. But this proposed method is not well suited for the removal of salt and pepper noise from the original image. Salt and Pepper Noise Removal[9] Images may be corrupted by salt and pepper impulse noise due to noisy sensors or channel transmission errors. A denoising method by detecting noise candidates and enforcing image sparsity with a patch-based sparse representation is proposed. Compared with traditional impulse denoising methods, including adaptive median filtering, total variation and Wavelet, the new method shows obvious advantages on preserving edges and achieving higher structural similarity to the noise-free images. Parallel Edge Preserving Algorithm for Salt and Pepper Image Denoising [10] this paper a two-phase filter for removing "salt and pepper" noise is proposed. In the first phase, an adaptive median filter is used to identify the set of the noisy pixels; in the second phase, these pixels are restored according to a regularization method, which contains a data-fidelity term reflecting the impulse noise characteristics.

In this paper decompose the image using discrete wavelet and then applied genetic algorithm for feature selection and threshold for noise removal. The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Speckle noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The method used in this paper can efficiently remove a variety of noise while preserving the image information well.

The remainder of the paper is organized as follows: In Section II, the overview of proposed method is presented. In Section III, the proposed method is specifically depicted, including its design idea and practical implementation approach. In Section IV, the performance of the proposed method is evaluated. Finally, conclusions are made in Section V.

II. IMAGE DENOSING USING GENETIC AND THERSHOLDING ALGORITHM

The overall block diagram of the proposed method is shown in Fig.1. In this paper decompose the image using discrete wavelet and then applied genetic algorithm for feature selection and threshold for noise removal. The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. In this paper Visu Shrink, Neigh Shrink, Sure Shrink and Modineighshrink.

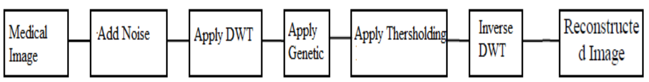

Fig. 1. Overall Block Diagram of Proposed Methods

Min-Max Shrink are used. De-noising of natural images corrupted by Speckle noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The further details of these modules are discussed below:

III. THE PROPOSED IMAEG DENOISING PRCODURE

A. Input Image Choosing

This is the first step of the proposed method. In this step the input image is get from the user via opendialog box control.

B. Apply Noise

This is the second step of the proposed method. In this step the input is corrupted by noise. Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.
In this paper two types of noises are used. They are Speckle Noise and Poisson Noise.

Speckle is a granular 'noise' that inherently exists in and degrades the quality of the active radar, synthetic aperture radar (SAR), medical ultrasound and optical coherence tomography images. The vast majority of surfaces, synthetic or natural, are extremely rough on the scale of the wavelength. Poisson noise is a type of electronic noise which can be modeled by a Poisson process. In electronics shot noise originates from the discrete nature of electric charge. Shot noise also occurs in photon counting in optical devices, where shot noise is associated with the particle nature of light.

C. Apply Wavelet Transform

This is the third step of the proposed method. In this step the noisy image is decomposed using discrete wavelet transform. The Discrete Wavelet Transform (DWT) of image signals produces a non- redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using DWT. These are also known by other names, the sub-bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the

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wavelet coefficients in the high frequency levels need to be thresholded. Several families are available in DWT. Among those this paper consider four families such as coif4, coif5, rbio6.8 and sym8.

D. Feature Selection using Genetic Algorithm

This is the fourth step of the proposed method. In this step the noisy wavelet coefficient feature are selected using genetic algorithm. In a genetic algorithm, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called phenotypes) to an optimization problem, evolves toward better solutions. Solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. The algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

A typical genetic algorithm requires: A genetic representation of the solution domain

- A fitness function to evaluate the solution domain.
- A standard representation of the solution is as an array of bits. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case.

Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming. Objective Function of Genetic Algorithm: The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. For instance, in the knapsack problem, one wants to maximize the total value of objects that can be put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The fitness of the solution is the sum of values of all objects in the knapsack if the representation is valid or 0 otherwise. In some problems, it is hard or even impossible to define the fitness expression; in these cases, interactive genetic algorithms are used. Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover, and inversion and selection operators.

E. Apply Thersholding

This is the fifth step of the proposed method. In this step the image denoised by using thersholding approach. Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule. The following are the methods of threshold selection for image de-noising based on wavelet transform.

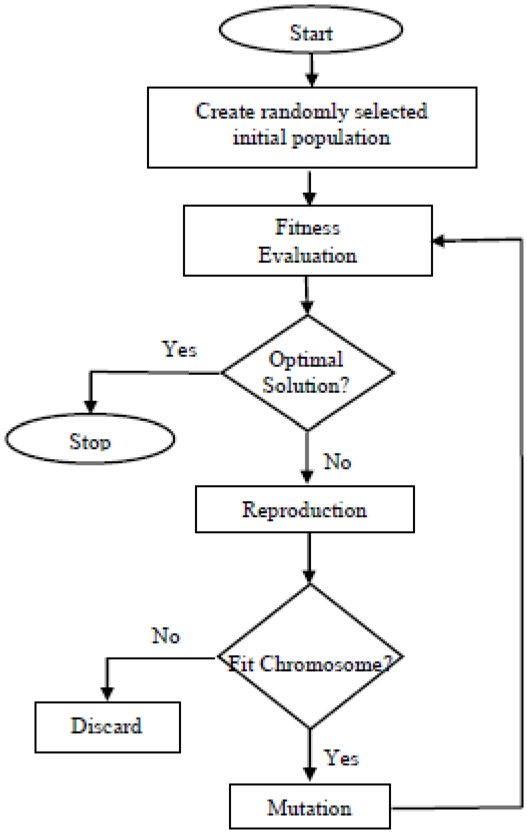

Fig.2. Flow Chart of the Genetic Algorithm

Method1: SureShrink is a thresholding technique in which adaptive threshold is applied to sub band, but a separate threshold is computed for each detail sub band based upon SURE (Stein.s Unbiased Estimator for Risk), a method for estimating the loss in an unbiased fashion. The optimal λ and L of every sub band should be data-driven and should minimize the Mean Squared Error (MSE) or risk of the corresponding sub band. Fortunately, Stein has stated that the MSE can be estimated unbiased from the observed data. Neighshrink can be improved by determining an optimal

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threshold and neighbouring window size for every wavelet sub band using the Stein"s Unbiased Risk Estimate (SURE). For ease of notation, the Ns noisy wavelet coefficients from sub band s can be arranged into the 1-D vector. Similarly, the unknown noiseless coefficients from subband „s" is combined with the corresponding 1-D vector. Stein shows that, for almost any fixed estimator based on the data , the expected loss (i.e risk) $E\{\|\underline{\theta}^s - \theta^s\|_s^2\}$ can be estimated unbiasedly. Usually, the noise standard deviation σ is set at 1, and then

$$E\{\|\bar{\theta}_s - \theta_s\|_2^2\} = N_s + E\{\|g(w_s)\|_2^2 + 2\nabla . g(w_s)\}$$

$$g(w_s) = \{g_n\}_{n=1}^{N_s} = \bar{\theta}_s - w_s, \nabla . g \equiv \sum_n \partial g_n / \partial w_n$$

Method 2: Visushrink Threshold T can be calculated using the formulae, T= σ√2logn2.This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients. All the rest wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaptation. However, it exhibits visual artifacts.

Method3: Neighshrink Let d(i,j) denote the wavelet coefficients of interest and B(i,j) is a neighborhood window around d(i,j). Also let S2=Σd2(i,j) over the window B(i,j). Then the wavelet coefficient to be thresholded is shrinked according to the formulae, d(i,j)= d(i,j)* B(i,j) where the shrinkage factor can be defined as B(i,j) = (1- T2/ S2(i,j))+, and the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative.

Method 4: Modineighshrink During experimentation, it was seen that when the noise content was high, the reconstructed image using Neighshrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the PSNR of the reconstructed image using wiener filtering. The de-noised image using Neighshrink sometimes unacceptably blurred and lost some details. So that it has been processed by K-VSD algorithm and then threshold for the shrinkage the coefficients. In earlier methods the suppression of too many detail wavelet coefficients. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by B(i,j) = (1-(3/4)*T2/ S2(i,j))

F. Apply Inverse Wavelet Transform

This is the final step of the proposed method. In this step the inverse wavelet transform is applied and get the denoised image.

IV. PERFORMANCE ANALYSIS

A. Expiremental Images

Experiments were conducted on a group of medical images to verify the effectiveness of the proposed scheme. For the experimental purpose several standard, 512 × 512 images are taken. Some of these images are shown in Figure 2.

B. Performance Analysis

To evaluate the performance of the steganography techniques several performance metrics are available. This paper uses the PSNR to analyses the performance.

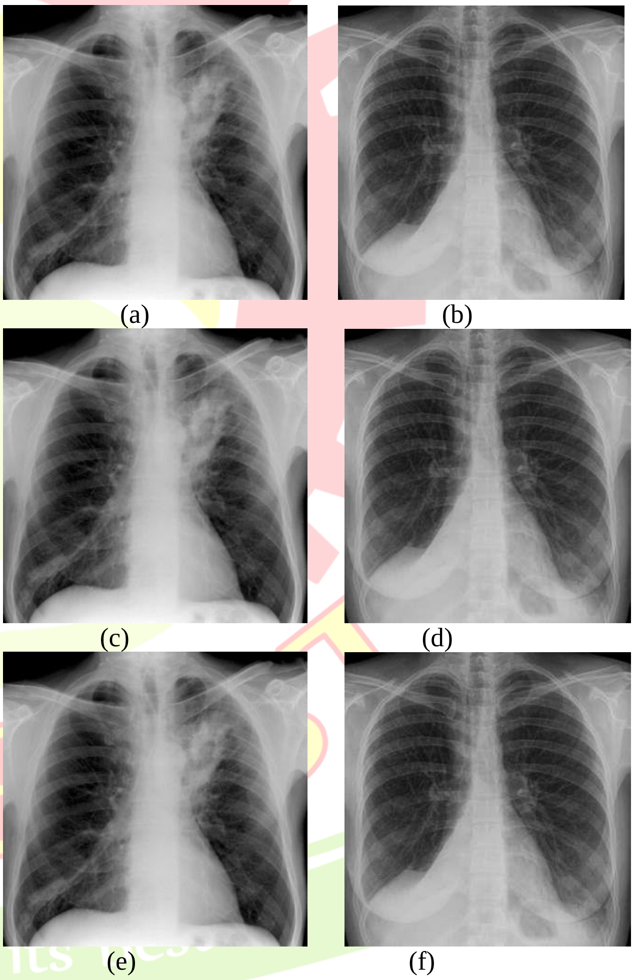

Fig. 2. Expiremental Images

1. Peak Signal-to-Noise-Ratio

The peak signal-to-noise ratio (PSNR) is used to evaluate the quality between the denoised image and the original image. The PSNR formula is defined as follows:

$$\mathrm{PSNR} = 10 \times \log 10 \frac{255 \times 255}{\frac{1}{H \times W}\sum_{x=0}^{H-1}\sum_{y=0}^{W-1}[f(x,y) - g(x,y)]^2} \mathrm{dB}$$

where H and W are the height and width of the image, respectively; and f(x,y) and g(x,y) are the grey levels located at coordinate (x,y) of the original image and denoised image, respectively.

To analysis the performance of the three methods by using the performance metrics which are mentioned above. This is shown in the below tables and graphs

Poisson Noise Variance		0.02	0.04	0.06	0.08
Wavelet Type	Threshold Type				
coif4	Visu	27.29	25.15	23.63	21.37
coif5	Neigh	30.07	27.82	25.83	23.64
rbio6.8	Sure	28.49	26.23	24.65	22.23
sym8	Modineigh	24.52	22.73	20.75	18.96

Gaussian Noise Variance		0.02	0.04	0.06	0.08
Wavelet Type	Threshold Type				
coif4	Visu	24.94	22.80	21.28	19.02
coif5	Neigh	27.72	25.47	23.49	21.29
rbio6.8	Sure	26.14	23.88	22.31	19.88
sym8	Modineigh	22.17	20.38	18.40	16.61

V. CONCLUSION

In this paper decompose the image using discrete wavelet and then applied genetic algorithm for feature selection and threshold for noise removal. The image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Speckle noise and Poisson using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The method used in this paper can efficiently remove a variety of noise while preserving the image information well. It is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR. The experimental results shows its better performance compared with some existing methods.

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