

A COMPARATIVE STUDY ON IMAGE DENOISING WITH ITS CLASSIFICATION AND APPLICATIONS

Satendra singh bhadoriya¹, Rajeev kumar singh²
^{1,2}Department of CSE & IT, MITS, Gwalior, (India)

Abstract

Image denoising forms the pre-processing step in the field of photography, research, technology and medical science, where a somehow image has been degraded and needs to be restored before further processing. Image denoising is still a challenging problem for researchers as image denoising causes blurring and introduces artifacts. Different types of images inherit different types of noise and different noise models are used to presenting different noise types. Denoising method tends to be problem specific and depends upon the type of image and noise model. Image restoration is the process of restoring the degraded or corrupted image back to its original form. Noise is added in the image while sending an image from one place to another via satellites, wireless, or during image acquisition process. It is a process to recover images from distorted to its original image. In this paper, we study about the type of noise, classification of image denoising techniques.

Keywords—Noise, Spatial filtering, Transform domain filtering, Linear filtering.

I. Introduction

The image processing is a technique that enhances the raw images received from cameras or pictures taken in day-to-day life for many applications, but there are still some bottlenecks on which researchers have their focus. Unfortunately, the image taken by digital cameras could be affected by noise due to random variation of pixel elements in the camera sensor. There are so many causes of noise by which digital images are corrupted [1] such as malfunctioning pixels in camera sensors, faulty memory locations in hardware or transmission of the image in a noisy channel and some other causes also. Noise represents unwanted information which destroys the image quality. It also affects the accuracy of many image processing applications such as image segmentation, image classification, edge extraction, image compression, etc[1].

Images are fashioned to show useful information. The original images are often ruined due to some disorder in image acquisition. In the image processing field, image restoration plays a vital role in order to acquire the quality image from a noisy or corrupted image. Denoising is also image restora-

tion method which is used to eliminate the noise present in the input image. Image quality is flawed by the redundant information which is nothing but the noise and they are occurring by an external disorder. The key intention of image restoration is to balance the defects which will be altering the original input image. Inpainting and interpolation are image restoration methods to get a better quality image. The digital image inpainting was first coined by Bertalmio et al. [2]. Removals of missing or broken portions of the images or videos are often in the image restoration. Inpainting has abundant applications for restoring the damaged painting and photographs by replacing the selected things [3] -[9]. The main objective is to repair the mislaid or scratched portions of an image so that it is possible to attain a visually clearer image and its uniqueness is achieved. It can also remove the unwanted things and writings present in the image and it can be removed by first marking the region in the image that has to be inpainted.

Loss of quality of image during transmission over channel and compression techniques (JPEG compression, JPEG-2000 compression, etc.) has been a major disadvantage because the viewers are unable to get the complete satisfaction. Hence, the demand for image restoration and quality assessment in recent trends is increasing [13]. The most accurate method of evaluating an image is a subjective evaluation. Subjective evaluation provides quality evaluation results as mean opinion scores. When evaluating a large set of images, Subjective evaluation is time-consuming and a complex one. In order to overcome the above said difficulties, Objective evaluation is preferred over subjective evaluation. Objective evaluation is evaluated using certain algorithms which are classified into three types based on metrics. They are Full reference metrics (FR metrics), Reduced-reference metrics (RR metrics) and No-reference metrics (NR metrics). In the evaluation process, the metrics will vary depending on the effective utilization of the reference image. Full reference metrics make full use of the reference image and compares it with the distorted format of the reference image. Reduced-reference metrics makes use of partial information about reference image and performs a comparison. In No-reference metrics, image does not make use of the reference image. In order to assess the quality of an image, the following steps are to be followed: (a) Image noising (b) Image restoration using filters (c) Comparison of the original image with restored image using RR metrics. In literature, a significant research effort has been taking place in developing objective image quality measures to mimic human visual system's perception more closely. The well-

known algorithm SSIM (Structural Similarity) is also reported in the literature and based on structural degradation assumptions which can be equated to the loss of visual quality. The visual signal-to-noise ratio detects with the ability of distortions and structural degradation based on the global precedence [14]. Several transform-based FR methods have also been proposed in the literature, such as DCT and wavelets, discrete orthogonal transforms contourlet transform based on frequency domain transforms [15]. The basic objective of these methods is to compare the transformed image signal components of reference and distorted images. This transformation will usually help in better representation of the image signals [16]. The most important factor in image restoration is a phase. Several works on phase have been done and it is concluded that phase provides more significant details regarding the image. The edges can be detected more efficiently at points of maximum phase congruency.

II. Types of Noise

The noise is characterized by its pattern and with its probabilistic characteristics. There is a wide variety of noise types while we focus on the most important types, they are; Gaussian noise, salt and pepper noise, poisson noise, impulse noise, speckle noise.

A) Gaussian Noise

Gaussian noise is the statistical noise which has its probability density function equal to that of a normal distribution, which is called as the Gaussian distribution. In the different words, the noise values can take on being Gaussian-distributed. A different case is white Gaussian noise, values at any pair of the times are identically distributed and also statistically independent. In applications, Gaussian noise is normally used as additive white noise to the yield additive white Gaussian noise[10].

$$g(x, y) = f(x, y) + n(x, y) \quad (1)$$

Where $g(x, y)$ is the output of the original image function $f(x, y)$ corrupted by the additive Gaussian noise $n(x, y)$.

Probability density function for Gaussian noise given below.

$$p(g) = \sqrt{\frac{1}{2\pi\sigma^2}} e^{-\frac{(g-\mu)^2}{2\sigma^2}} \quad (2)$$

Where g represents the grey level, μ the mean value and σ the standard deviation.

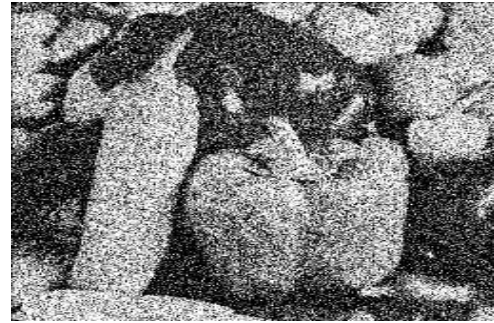


Fig1:Gaussian noise

B) Salt And Pepper Noise

Pepper and Salt noise are a form of the noise classically seen on the images. Salt and pepper noise represents itself as randomly happening black and white pixels. A real noise reduction technique for this kind of noise includes usage of the median filter, contra harmonic mean filter or a morphological filter. Pepper and Salt noise creeps into images in circumstances where quick transients, such as defective switching, take place. Salt and pepper noise is random in nature, it distributed randomly in the image b pixel values [11].



Fig 2: Salt and pepper noise

C) Poisson Noise

Poisson noise is induced by the nonlinear response of the image detectors and recorders. This type of noise is image data dependent. This term arises because detection and recording processes involve random electron emission having a Poisson distribution with a mean response value. Since the mean and variance of a Poisson distribution are equal, the image dependent term has a standard deviation if it is assumed that the noise has a unity variance[10].

Probability density function for Poisson noise given below.

$$f(X|\lambda) = \frac{\lambda^x}{x!} e^{-\lambda}; \quad x=0,1,2,3,\dots \quad (3)$$

e is Euler's number ($e = 2.71828\dots$), $k!$ is the factorial of k , The positive real number λ is equal to the expected value of X and also to its variance.

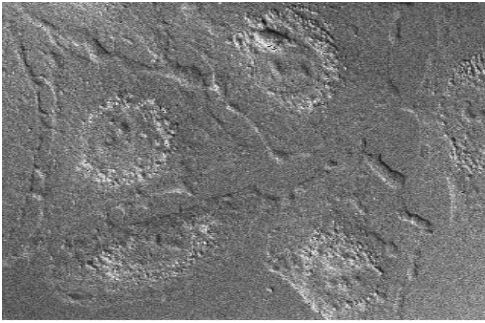


Fig 3: Poisson noise

D) Impulse Noise

Impulse noise is an acoustic noise type which contains unwanted, almost instantaneous (thus impulse-like) sharp noises (like pop and clicks). The noises of the type are typically caused through electromagnetic interference, on the recording disk scratches, and ill synchronization in the communication and digital recording. High levels of, such a noise (200 + Decibels) may harm internal organs, while 180 Decibels are sufficient to damage or destroy human ears[12].

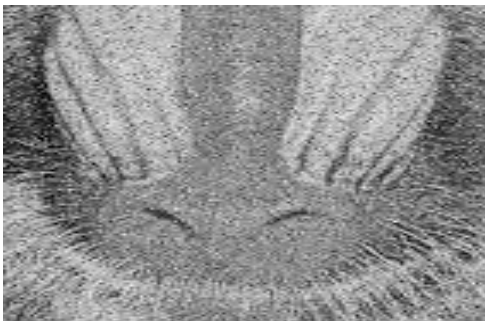


Fig 4: Impulse noise

E) Speckle Noise

Speckle is a complex phenomenon, which degrades image quality with a backscattered wave appearance which originates from many microscopic diffused reflections that passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. This type of noise occurs in almost all coherent systems such as SAR images, Ultrasound images, etc. The source of this noise is random interference between the coherent returns. The speckle noise follows a gamma distribution [17]. Thus, denoising or reducing the noise from a noisy image has become the predominant step in medical image processing. For the quality and edge preservation of images, we have taken different denoising techniques into consideration. speckle noise comes into multiplicative noise model[6].

$$g(x, y) = f(x, y) * n(x, y) \quad (4)$$

Where $g(x, y)$ is the result of the original image function $f(x, y)$ corrupted by the multiplicative noise $n(x, y)$



Fig 5: Speckle noise

III. Classification of Image Denoising Technique

There are two categories for image denoising:

- (a) Spatial filtering methods.
- (b) Transform-domain filtering methods.

A. Spatial Filtering

This can be divided into Linear and Non-Linear filter and this is the traditional method to remove the noise from images.

a) Nonlinear Filters

In Non-Linear filters, noise can be removed without identifying it exclusively. It employs a low-pass filtering on the assumption that noise always occupies a higher region of spectrum frequency. It removes the noise to a very large extent, but at the cost of blurring of images. Rank conditioned selection [15], weighted median, relaxed median have been developed over recent years to cover up some of the drawbacks.

b) Linear Filters

The optimal linear filter for Gaussian noise is the mean filter in terms of mean square error. It also tends to destroy the edges which are sharp, destroy lines and other details of the image. It doesn't perform well in case of signal-dependent noise. It is the method of choice in situations when only additive noise is present. destroy lines and other fine details of image. It includes Mean filter and Wiener filter. A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error.

B. Transform-domain filtering

These methods can be subdivided according to the basis functions.

a) Spatial Frequency Filtering

It refers the use of the low-pass filters applying FFT (Fast Fourier Transform). The removal of noise is done by adapting a frequency domain filter and deciding a cutoff frequency when the component of noise are decorrelated from the useful signal. These methods are time consuming and dependent on cutoff frequency. Furthermore, in the processed image they create artificial frequencies[18].

b) Wavelet Domain Filtering

In wavelet domain, filtering methods are divided into linear and nonlinear methods.

i. LINEAR FILTER

If the signal corruption can be modeled as a Gaussian process, Linear filters such as Wiener filter can give the optimal result and mean square error (MSE) [19]. Is the accuracy criterion. However, if we design a filter on this assumption, this results in a filtered image which is very displacement than the original noisy signal even though it considerably MSE reduces. In the wavelet domain spatially adaptive Wiener Filtering is proposed in which intrascale filtering is not allowed in any case.

ii. NON-LINEAR THRESHOLD FILTERING

The most researched domains in the denoising applying wavelet transform is the method of the non-linear coefficient thresholding based. This exploits the fact of the sparsity problem of wavelet transform and maps white noise in a signal domain to the transform domain white noise. Thus, white signal energy is more concentrated into transforming domain, noise energy cannot be accumulated. So, this is the very effective method of noise removal from the signal. The method which removes the small coefficients while others are untouched is known as Hard Thresholding. In this process, certain blips occurred which are also known as Artifacts which shows the unsuccessful attempts to remove moderately large noise coefficients. To cover the demerits of Hard Thresholding, Wavelet transforms soft thresholding was also presented in. In this, the coefficients greater than the threshold are limited through the absolute threshold value. Techniques other than soft thresholding are semi-soft thresholding and Garrot Thresholding[16].

a. Non adaptive Thresholds

VISU Shrink is the non-adaptive universal threshold which is completely dependent on the number of data points. It suggests the best presentation in terms of the MSE when the pixel number reached infinity. It yields the smooth images because its threshold value is quite large due to its dependency on the numerous pixels in the image[17].

b. Adaptive Thresholds

SUREShrink performs better than VISUShrink. Cross-validation [18] replaces wavelet coefficient with the average of

its neighbors to minimize the component, i.e. generalized Cross validation (GCV) which provides the optimum threshold for each and every coefficient.

One assumption that can be possible when we distinguish the noise and signal, the coefficient magnitudes are violated. Under these conditions, the spatial configuration of neighboring coefficients can plan a significant role in the classification of signal and noise respectively. Noise coefficients can scatter randomly while signal makes the meaningful configurations[18].

iii. NON-ORTHOGONAL WAVELET TRANSFORM

For decomposing signal to the offer visually improved the solution, Undecimated Wavelet transform (UDWT) can be used. It is shift invariant and avoids the defects and artifacts. Thus, largest improvements were there in the results but computations overhead make it less usable. Innormal hard/soft thresholding was concentrated to Shift Invariant Discrete Wavelet Transform. To obtain the number of basis functions, in the SIWPD (Shift Invariant Wavelet Packet Decomposition) is exploited. Using the principle of Minimum description length, finds the basis function which yields the smallest length. Then, thresholding is used to denoise the data. Use of multiwavelets is further explored which enhances the performance, but it increases the computational complexity. By applying more than one mother function to given data set, multiwavelets are generated. It possesses the properties like symmetry, short support, foremost is the higher order of vanishing moments. In the combination of invariance and multiwavelets shows the superior results with the Lena image[14].

iv. WAVELET COEFFICIENT MODEL

It focuses on exploring the multiresolution properties of the wavelet transform. Through signal observing across multiple resolutions, this method signals close correlation identifies at the various resolutions. This method gives the excellent results but it computationally less feasible due to cost and complexity. The Wavelet coefficients can be modelled either in the statistical or deterministic way.

a. Deterministic

It involves making of the tree structure of wavelet coefficients with each level in the tree representing the scale of transformation and also nodes representing wavelet coefficients. It is deterministic in nature, so this method provide significant output results on the PSNR and MSE value. It is adopted At the particular node, if the wavelet coefficient has a stronger presence than the signal, its presence is more pronounced at the parent nodes itself. If there is noisy coefficient, then its consistent presence is missing. In tree structure is tracked using wavelet local maxima. Another method is proposed by Dunoho using the wavelet coefficient method.

This wavelet coefficient method is also deterministic in nature[17].

b. Statistical Modelling

This approach explores some interesting properties of Wavelet Transform such as local correlation between neighbouring wavelets and multiple and global correlations between the wavelet coefficients etc. It has the inherent goal of improving the data of the image by using Wavelet Transforms. A review of statistical properties can be found in [21]. Two techniques are there to exploit the statistical properties of wavelet transforms which are:

c. Marginal probabilistic model

Many homogeneous local probability models have been developed by researchers in the field of image processing based on wavelet domain. The Wavelet coefficient distributions are highly disturbed and marked peak of zero at heavy tails. The commonly used models for modelling the wavelet coefficients are Gaussian Mixture Model (GMM) and Generalized Gaussian distribution (GGD) in GMM is simpler to use, but GGD is more accurate. The authors proposed a methodology in which has the wavelet coefficients assumed to be conditionally independent zero mean. The methods presented above require the noise estimate, which is very hard to achieve practically. Chang proposed the adaptive wavelet thresholding use for denoising of the images by analyzing the wavelet coefficients as a generalized Gaussian random variable where parameters can be calculated locally[22].

d. Joint Probabilistic Model

The efficient model for capturing interscale dependencies are Hidden Markov Model (HMM) whereas random Markov models are useful for capturing intrascale dependencies. Local structure, complexity is not well defined by the Random Markov model, whereas Hidden Markov model is able to capture higher order statistics in a much better way. On a model is based on which Wavelet coefficient's neighborhood, i.e. called as Gaussian State Mixture (GSM) is a product of Gaussian Random Vector and an independent hidden scalar multiplier. Another approach is used by Jansen and Bulthel for wavelet a coefficient that uses a Markov Random Field model. A drawback of the HMT is the computational burden of the stage of training. To overcome the drawback of HMT, a simplified approach uHMT, was used[23].

e. Data-adaptive transforms

Now-a-days, a new method called Independent Component Analysis (ICA) has gained the worldwide attention. In denoising non-gaussian data, the ICA method was successfully implemented. One property of ICA is to assume the signal which is a non-Gaussian, which is helpful to denoise the images with Gaussian and Non-Gaussian distribution.

The demerit of ICA based as compared to the wavelet based method is the cost of computation because it uses the sliding window and requires the noise-free data sample or at least some frames of the image or scene. It is very difficult to find the noise-free data in some applications.

IV. Literature Review

In this paper[24] introduce image restoration using interpolation, in painting and denoising the noisy image by iterative methods. The main task of image restoration is to capture a noisy image and estimating the original image. The important scheme of image restoration is to stabilize the defects which can corrupt the original input image. In this paper, restoration of an image can be implemented by three methods. First, a certain level of noise is added to the input image and the noise can be reduced by an iterative method. In this, noise level added is made constant and iteration is performed. Second, the damaged image is selected and the image quality is restored by estimating the local properties of the image (in painting). Third, restoration is done by using interpolation of up and down sampling. For every method, the quality metrics like PSNR and SSIM are calculated. From these PSNR and SSIM values, the tabulation and performance graph are obtained. The improved efficiency of image restoration using image denoising, interpolation and in the painting is achieved and they are compared with all other techniques. Convergence time is also reduced when compared with other techniques.

In this paper[25] propose a new image denoising scheme that is an integration of a content-adaptive guided filter and a collaborative Wiener filter. The proposed scheme consists of two steps. First a content-adaptive guided filter, which smoothes image based on spatial similarity within a local window, is applied. The content adaptive guided filter can efficiently preserve edges while smoothing noise. A preliminary estimation of noise-free image can be obtained by the content-adaptive guided filter. In the second step, a patch-grouping based collaborative Wiener filter is adopted to exploit non-local similarity, and outputs final denoised image. Compared to the state-of-the-art denoising scheme, BM3D, the proposed method is more efficient in computation. Moreover, simulation results have shown that the proposed method can achieve comparable PSNR values and better visual quality on denoising of textural images.

In this paper[26] present that Enhancing the sharpness and reducing the noise of blurred, noisy images are crucial functions of image processing. Widely used unsharp masking filter-based approaches suffer from halo-artefacts and/or noise amplification, while noise- and halo-free adaptive bilateral filtering (ABF) is computationally intractable. In this study, the authors present an efficient sharpening algorithm inspired by guided image filtering (GF). The author's proposed adaptive GF (AGF) integrates the shift variant technique, a part of ABF, into a guided filter to render crisp and

sharpened outputs. Experiments showed the superiority of their proposed algorithm to existing algorithms. The proposed AGF sharply enhances edges and textures without causing halo-artefacts or noise amplification, and it is efficiently implemented using a fast linear-time algorithm.

In this paper[27]Propose a single-frame super-resolution algorithm using a finite impulse response (FIR) Wiener-filter, where the correlation matrices are estimated using the nonlocal means filter. The major contribution of this work is to make use of the nonlocal means-based FIR Wiener filter to form a new iterative framework which alternately improves the estimated correlation and the estimated high-resolution (HR) image. To minimize the mean squared error of the estimated HR image, and tried to optimize several parameters empirically, including the hyper-parameters of the nonlocal means filter by using an efficient offline training process. Experimental results show that the trained iterative framework performs better than the state-of-the-art algorithms using sparse representations and Gaussian process regression in terms of PSNR and SSIM values on a set of commonly used standard testing images. The proposed framework can be directly applied to other image processing tasks, such as denoising and restoration, and content-specific tasks such as face super-resolution.

In this paper[28] present that Image denoising is the process to remove the noise from the image naturally corrupted by the noise. The wavelet method is one among various methods for recovering infinite-dimensional objects like curves, densities, images, etc. The wavelet methods are based on shrinking the wavelet coefficients in the wavelet domain. A denoising approach basing on dual tree complex wavelet and shrinkage with the Wiener filter technique (where either hard or soft thresholding operators of dual-tree complex wavelet transform for the denoising of medical images are used). The results proved that the denoised images using DTCWT (Dual Tree Complex Wavelet Transform) with Wiener filter have a better balance between smoothness and accuracy than the DWT and are less redundant than SWT (Stationary Wavelet Transform). And used the SSIM (Structural Similarity Index Measure) along with PSNR (Peak Signal to Noise Ratio) and SSIM map.

V. Result Analysis

PSNR:

The Peak Signal to Noise Ratio (PSNR) is the ratio between maximum possible power and corrupting noise that affect representation of image. PSNR is usually expressed as decibel scale. The PSNR is commonly used as measure of quality reconstruction of image. High value of PSNR indicates the high quality of image.

$$PSNR = 10 \cdot \log_{10} \left[\frac{(255)^2}{MSE} \right] \quad (5)$$

MSE:

Mean Squared Error (MSE) which is for two $m \times n$ monochrome images I and K , where one of the images is restored image and the other is original image .

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \|I(i, j) - K(i, j)\|^2 \quad (6)$$

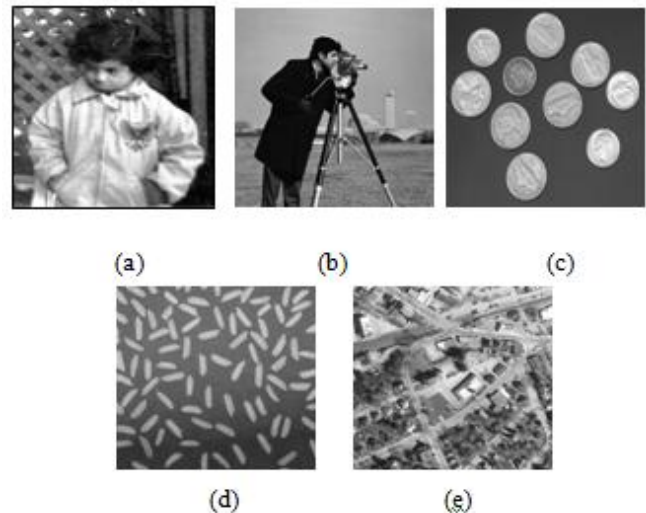


Fig 1: Image Dataset

Table1: Shows the PSNR and MSE values on images with Guided and Wiener Filter

IMAGE	Guided Filter MSE	Wiener Filter MSE	Guided Filter PSNR	Wiener Filter PSNR
(a)	25.6329	19.4256	30.5854	32.0563
(b)	17.9980	19.7444	31.7814	31.1602
(c)	13.2965	11.5053	33.4049	34.4053
(d)	26.1108	22.2865	30.8855	31.5399
(e)	40.1413	43.2788	28.2429	27.5165

VI. Comparison on Different Methods and Noise

In the table below a comparative study on different algorithms and noise has been done, that shows which method gives better results. For Gaussian noise, different methods give better results in terms of improved PSNR and less Noisy image.

Algorithm/Method	Technique/Component used	Type of noise	Results	Applications
Linear Minimum Mean Square Error Estimation Framework[30].	Directional Interpolator	Gaussian Noise	<ol style="list-style-type: none"> 1. minimize Interpolation Artifacts 2. Edge and Structure Preservation 3. moderated output 	All Image Acquisition systems
Bayesian two complementary discontinuity measure[31].	Spatial and contextual discontinuity measures Local in homogeneity measure	Gaussian Noise	<ol style="list-style-type: none"> 1. Improved PSNR 2. Effective noise reduction 3. Edge structure preservation 	Electron Microscopy
Wavelet-based Three scales Dependency[32].	Dua- tree complex wavelet coefficients	Gaussian Noise	<ol style="list-style-type: none"> 1. Approximate shift Invariance 2. Good directional selectivity 3. Highly competitive 	Multimedia applications
Adaptive Multi resolution[33].	Non-local Mean Filter	Gaussian and Rician Noises	<ol style="list-style-type: none"> 1. Effective qualitative and quantitative noise 2. Classic fine detail preservation 	Magnetic Resonance Imaging, Fibre tracking
Decision based variational method[34].	Adaptive center weighted median filter	Impulse noise	<ol style="list-style-type: none"> 1. All the noisy parts are restored 2. Good vision measurement 3. Good quantitative measurement 4. Fast performance 5. Easy to implement 	Real-time applications
Non-convex, non-smooth Hilter-Sobolov Norm[35].	Variable splitting and penalty techniques		<ol style="list-style-type: none"> 1. Better denoising 2. Better deblurring 3. Better Decomposition 	Real and Synthetic Images
Wavelet domain processor[36].	(2D GARCH) Two-dimensional generalized autoregressive conditional Heteroscedastic model	Speckle noise	<ol style="list-style-type: none"> 1. Increased flexibility 2. Improved restoration 3. Improvement in image characteristics 	Ultrasound images

VII. Conclusion

In this paper present a survey on image denoising approach and comparative study on various techniques and types. As images are very important in each and every field so Image Denoising is an important preprocessing task before further processing of image like segmentation, feature extraction, texture analysis etc. In image denoising different types of noises that can corrupt image and types of filters by which recover noisy image. Different filters show different results after filtering. Some filters degrade image quality and remove edges. Performance of denoising algorithms is measured using quantitative performance measures such as Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE) as well as in terms of visual quality of the images

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Biographies



Satendra Singh Bhadoriya has received the B.E. degree in Computer Science & Engineering, from Maharana Pratap college of Technology, Gwalior,India in 2010. Currently he is pursuing M.Tech (Computer Science & Engineering) from MITS, Gwalior. His research area includes Image denoising.



Prof. **Rajeev Kumar Singh** is working as assistant Professor, Department of Computer Science Engineering & Information Technology, MITS, Gwalior,India. His passion is to contribute in research activities of Science & Technology. His teaching and research include Image Processing and software engineering.