A Review on Image De-Noising Techniques

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Abstract - *Images are used to either store or display to convey meaningful information. Many times, these produced images exhibit a degraded class of their original image, the causes may be an imperfection in capturing and processing steps. There are many types of image degradations, such as noise, geometrical degradation, illumination and colour imperfection and blur. The rectification of these image degradations is important for its subsequent processing stages. It is a challenging task to eliminate the mixed noise because; the noise distributed is highly non-linear. Additive White Gaussian Noise and Impulse Noise are having dissimilar characteristics and these are the most faced mixed noise. Many numbers of methods are proposed to reduce these mixed noises, a sparse representation via a sequence of Additive White Gaussian Noise as well as Impulse Noise reduction. We begin with the types of noise associated with captured images, then the different approaches in denoising it.*

Key Words: **Additive White Gaussian Noise, Impulse Noise, Image Denoising, CNN Methods, FFDNet Method.**

1. INTRODUCTION

At present, with the advancement of imaging and display technology, it is possible to display images clearly as in original pixels and easy to distinguish noise pixels by bare human vision. It is estimated that 1.2 trillion digital images are captured every year, which gives thrust for perfect images [1-3]. Images are frequently impacted with noise during, picture acquisition or transmission stages. The two most popular types of noise in an image are White Gaussian noise as well as Impulse noise. The origins of White Gaussian Noise are sensor temperature; but mostly ambient lighting conditions, whereas sensor failure or transmission errors are the sources for an Impulse Noise. These two types of noise have quite different distributions, making it a very tough task to remove. The major causes for this are since individual pixel grey levels are extremely susceptible to change. Other considerable factors affecting negatively are the photography environment and quality of imaging sensors [4-6].

The high-frequency nature of noise, image edge and image pixels are making it a hard accomplishment to denoise. This may result in loss of some pixel details in the denoised image [2]. Hence it makes image denoising the finest problem, even though many researchers had worked for a longer time, the problem is still evident. The primary reason could be due to its mathematical aspect. When it comes to removing noise from a corrupted image, Additive Gaussian Noise is commonly used. It is used to model thermal noise [5]. The Wavelets and Kernel regression are proposed for its removal, due to its mathematical traceability. There are majorly 4 types of image noise as discussed below:

1.1 Gaussian Noise

Gaussian noise is also termed as statistical noise, possessing the probability density function; it is same as the normal distribution. This surfaces in devices like detector and amplifier, and hence this is also referred as Electronic Noise. The Gaussian random variable z's probability density function p is described as:

$$PG(z) = \frac{1}{\sigma\sqrt{2\pi}} e - \frac{(z-\mu)^2}{2\sigma^2} \qquad (1)$$

In the above term, σ is standard deviation. This parameter has a direct relationship with noise magnitude.

1.2 Impulse Noise

Imperfection in image capturing device hardware or the camera sensor causes this type of noise. A portion of the original image's pixels will be replaced, which takes only two finite values. Impulse noise is divided into three categories. Salt noise, adds a 255-pixel value, creating random brightness. Pepper noise, it adds a 0-pixel value, creating random dark. Finally, Salt and Pepper noise, the addition of random bright and random dark to an image.

1.3 Poisson Noise

The statistical character of EM waves like x-rays and gamma rays reveals this noise. These rays are passed across the human body for medical imaging from its source, which is having random fluctuations of photons. Hence its captured image is subjected to spatial and temporal randomness.

1.4 Speckle Noise

In medical ultrasound imaging, speckle noise is an intrinsic property; which leads to degradation of image resolution and contrast, which in turn, affects diagnostic values. Hence it is extremely important to reduce speckle noise in ultrasound-based medical imaging.

2. LITERATURE REVIEW

The purpose of this review taken is to identify the research gap by analyzing current and previous research works in the area of image denoising.

2.1 Spatial Domain Filtering

To enhance an image filtering technique are applied. In spatial domain filtering the current pixel obtained value depends on both itself and its neighboring pixels. As a result, the value of any pixel in the processed image is calculated as follows: adopting some algorithms to the nearby input pixel. A pixels nearby is some set of pixels; their location is relative to that pixel [2, 4, 18].

Spatial filtering is largely applied for image denoising, it is further classified as linear and nonlinear filters. Majorly, linear filters are employed for the removal of noise in the spatial domain; but it has a drawback that is incapable to protect image textures. To remove Gaussian noise, Mean filtering techniques were used, but it tends to over smooth the images. As a remedy to this problem, Wiener Filtering techniques were proposed by researchers, again this filtering also proved inefficient by blurring sharp edges. A nonlinear filtering technique, namely Median and Weighted Median filters are proven to be effective in removing noises.

Bilateral filtering seems to be another filtering approach that has been proposed for image denoising [10]. In this technique, each pixel value is replaced with a weighted average of the value of the pixel intensity of the neighboring pixel. The only limitation of bilateral filtering is concerned with its efficiency, takes a long time when the kernel radius is more. From literature we observed that spatial filters are effective in noise removal, but it tends to blurring images and loosing sharp edge details.

2.2 Variational denoising methods

In image processing, we always represent images in the form of mathematical functions. These functions are called either brightness or intensity; they can be continuous or discrete in nature [2, 7, 12, 18]. The variational denoising technique is a popular and promising one; it is introduced by Rudin with his proposed model ROF. This model, on the other hand, is exclusively used to reduce Gaussian noise. The denoising methodology uses picture priors and the minimization of the energy function E to calculate denoised images. The E function must first be obtained from the noise image y, and then a mapping process must be used. By decreasing E, we can then reassemble a denoised image.

$$\hat{x} = \arg\min E(x) \tag{2}$$

Main inspiration to this method is Maximum a Posteriori Probability of Bayesian Statistics.

2.3 Sparse Representation

Sparse representation is based on a sparse matrix, where most of the matrix elements are Zero. In signal sparsity, the representation of a linear combination of a finite number of elements can be achieved and it can be achieved in transform domain sparse as well [6]. Normally expressed as

$$y = \sum_i a(i)\varphi(i) \tag{3}$$

Where a(i) is the indication coefficient of the signal x which can be found in the dictionary D. The presentation of many atoms as M x N matrix is known as dictionary D, and this is recognized as the absolute dictionary when N=M and as through absolute dictionary when N>M. The benefits of these dictionaries are its very helpful in representing more diverse data, selection of D plays a vital role in algorithms performance. K-singular Value Decomposition (K-VSD) dictionary learning algorithm can be used for generating a dictionary for sparse representation. It is a variant of the k-means clustering algorithm, updates atoms in dictionary for a better fit by continuously alternating between sparse coding on the current dictionary.

The denoising can be achieved by using sparse representation based on global training dictionaries and adaptive dictionaries. It is observed that sparse representation is the superior method for image denoising, and with K-VSD learning dictionary it performs even better results [6, 15, 20, 21]. Figure 1 (a, b, c) shows the output of sparse representation.

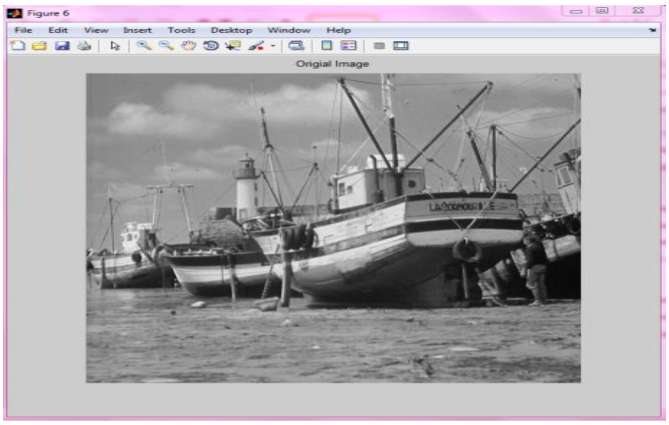

Fig -1: Denoising based on sparse representation (a)

Fig -1: Denoising based on sparse representation (b)

Fig -1: Denoising based on sparse representation (c)

2.4 Methods used for Filtering Operation in the Transform Domain

The technique, Fourier transform is used to create transform domain procedures and methods, later several other methods were introduced. Based on transform functions, transform domain filtering is classified as Data adaptive and Data less adaptive transform. Different types of filtering techniques used in the transform domain, such as Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Discrete Cosine Transform (DCT), Dual-Tree Complex Wavelet Transform (DT-CWT) and many more methods are proposed by researchers. Among these DT-CWT is the most promising method [2, 22]. The comparative analyses of these methods are listed in the following Table 1.

Table -1: Similarity between the wavelet transform domains

Methods/ Parameter	DCT	DWT	SWT	DT-CWT
PSNR	Lesser than all other	DCT<DWT < SWT, DT-CWT	DCT, DWT<SWT<DT-CWT	Greater than all
MSE	Greater than all	SWT, Dt-CWT<DWT <DCT	DT-CWT<SWT<DCT, DWT	Lesser than all
Loss of Information	Higher loss	SWT, DT-CWT<DWT <DCT	DT-CWT<SWT<DCT, DWT	Preserves more information
Advantage	• Fewer memory requirements • Simple	• Produces sharper images	• Reduced loss of information	• Shift invariance

2.5 CNN Based Denoising Methods

Concerning accuracy and robustness, ***CNN*** based image denoising method has shown prominently better result in comparison with sparse representation and patch-based techniques. The different layers of the CNN Model are described as follows; ***convolution layer*** carries out the filtering operation, ***Rectified Linear Unit (ReLU)*** an activation function, a Max pool layer to reduce the spatial dimensions [2,10].

The ***BM3D*** algorithm was used before introducing Neural Networks to the image denoising., in which depending on similarity image fragments are clubbed together is known as block matching [23, 25]. Whereas BM3D clubs' ***macroblocks***. Model-based approaches like BM3D and WNNM are efficient in managing image denoising challenges with variety of noise levels. However, they are tedious in optimization and it is not possible to use them directly on spatial variant noise.

One of the major challenges in adopting the deep learning technique in image denoising is about feeding image data into the neural network. If the given is in RGB format then the number of pixels would be having a count multiplied by 3, which may require a huge number of input nodes for neural network, this, in turn, increases network size and computational time requirements. To overcome this issue Convolutional Neural Networks (CNN) was proposed [23].

In computer vision and machine learning techniques, rank minimization has taken considerable attention, widely used is ***Nuclear Norm Minimization*** (NNM). Since there are few limitations in NNM, later advancement has indicated ***Weighted Nuclear Norm Minimization*** (WNNM) have a higher matrix rank approximation [24-27]. From the research work it has been noticed that WNNM, as applied to image denoising task, is not only shown PSNR improvements, but it also significantly retains the original image structure and reduces visual artifacts.

Denoising Convolutional Neural network (DnCNN), is designed to anticipate residual image, to improvise the training performance of DnCNN a batch normalization technique is used.

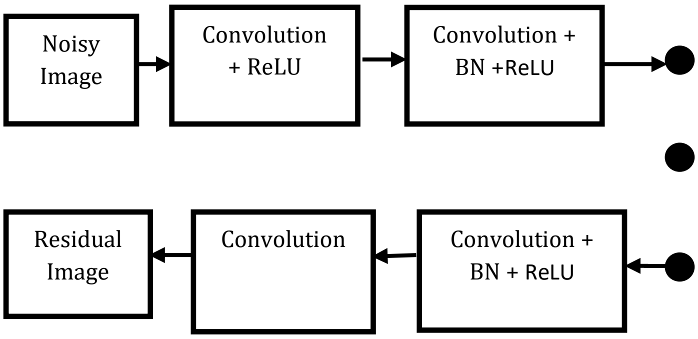

Fig -2: Building design of the Intense DnCNN [28]

The model shown in Fig - 2, is demonstrated with respect to blind Gaussian denoising. This system of technique used to extract the Gaussian noise from the unrecognized levels in the group of noises.

The discriminative learning methods are widely studied and applied to image denoising, but there are several limitations found on this; For each noise level, it must train a unique model additionally this is not flexible to handle spatially variant noise. To overcome these issues researcher has proposed a **Fast and Flexible Denoising Convolutional Neural Network** (FFDNet), which represents the input function, a configurable noise level map. FFDNet is represented in the form

$$x = F(y, M; \Theta) \quad (4)$$

in Eq. 4, M is named as 'noise level map'. As identified in the technique of DnCNN, ϴ varies for changes in noise level, whereas in FFDNet it is made unchangeable to the level of the noise. Therefore FFDNet, is a more versatile method to operate variety of levels in the noise using an individual network [26].

Table 2: Average PSNR Results [2]

Methods	BM3D	WNNM	DnCNN	FFDNet
σ = 15	31.07	31.37	31.72	31.62
σ = 25	28.57	28.83	29.23	29.19
σ = 50	25.62	25.87	26.23	26.30
σ = 75	24.21	24.40	26.64	24.74

3. CONCLUSIONS

Though many researchers had proposed several denoising methods for decades of years, the complexity and requirements are still in trend. In this review article, I have spread light on recent trends in image denoising and their advantages and limitations. The spatial domain filtering technique directly manipulates pixels of an image, this new type of method is not only simple but easy to implement, and it offers no robustness. The sparse representation is cheaper concerning space consumption. For the operations like low luminance enhancement, inequality adjustment and image denoising task the CNN is the most optimal choice, which gives a higher performance in all segments. The new CNN model, FFDNet has proved sound, secure, quick, powerful and more adaptable in handling different noise levels.

In the recent decade, we find deep learning technique is emerging rapidly, but it need not be a productive method to handle denoising task. The major cause for this assertion is due to the lack of image pairs available for training, most of the time simulated noisy images are used.

In this article various methods for image denoising are discussed, the identified future aim is an analysis of various noises is necessary since different types of noise need different methods to be employed for handling it.

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