International Journal on Engineering, Science and Technology
Volume 4, Issue 1, 2022 ISSN: 2642-4088

Medical Image Denoising Techniques: A Review

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Abstract: Medical imaging means the methods and procedures used for creating pictures of various parts of the human body for numerous clinical objectives. These images are constantly gets dirtied by noise during picture acquisition and transmission, resulting in low quality images. Noise is the unwanted signal which corrupts the important and desirable information. The noises can be categorized into different types based on their nature and origin. e.g. Gaussian, the impulsive and speckle noise etc. The removal of noise is very necessary for proper analysis and diagnosis. Filtering noise helps to recreate a high-quality image in digital image processing for further image processing such as segmentation of images, identification, recognition and monitoring, etc. There are various approaches to denoise medical images based on transform approach, machine learning, filtering method and statistical method. These techniques or approaches is subject to noise type exist in the image. To evaluate the denoising performance, parameters like SNR, PSNR etc. are used. This paper takes a review of current denoising techniques.

Keywords: Review, Medical, Image, Denoising

Introduction

The procedures and methods used to produce the human body images and its parts is called as Medical Imaging (MI). It is used for medical processes and analysis. It is also used in medical science which embraces the training of normal structure and function. In other words, it embraces biological imaging and comprises radiology, endoscope, thermograph etc. It is usually compared to radiology or "clinical imaging". Various medical imaging techniques are computed tomography (CT) for the imaging of X-rays, isotope Positron Emission Tomography (PET), MRI (magnetic resonance imaging) etc. These techniques are having many advantages as compare to other useful medical imaging approaches (*Ganguly et. al., 2010; Deserno 2011)* But, these images are often gets degraded by noise while acquiring and transmitting the pictures, leading to low quality images.

Noise is the undesirable signal which spoils the important and necessary information. So, the elimination of noise is very essential for correct analysis and diagnosis. Image noise reduction is a main pre-processing juncture in medical image analysis. The elementary purpose is to rebuild the original image from its corrupted image as precisely as possible and also to protect important features like edges and textures. (*Mohd. Ameen, Shah 2016*) To attain this, image noise reduction methods are widely studied in the image processing and proposed various denoising methods. Each method is having its own assumptions, advantages, and limitations.

Performance Evaluation Parameters in Image Denoising

Image quality measurement are having two methods. First method is having subjective approach and while second method is having objective approach. The image quality assessment (IQA) technique involve human beings to assess the quality of image. The ultimate users of most of the multimedia applications are human beings. So subjective valuation is considered the most correct and trustworthy technique for evaluating the image quality. But, this process is very slow, difficult and costly for practical purpose. So, the objective image quality metrics which automatically calculate the image quality is quite convenient. The objective IQA research purpose is to calculate the image quality which should be very close to the subjective assessment.

Objective quality or distortion valuation approaches are of two types. First approach is mathematically defined measuring parameters like Mean Square Error (MSE), Root Mean Square Error (RMSE) and Peak Signal-Noise Ratio (PSNR). Another approach is Human Visual System (HVS) properties. It embraces perceptual quality measures (*Thung 2010*).

RMSE is defined as follows: Suppose the real image, corrupted image and the denoised image be represented by i(m,n), c(m,n) and i'(m,n) respectively. Here, m and n represents the discrete spatial coordinate of the digital images. Let the images be of size PxQ pixels i.e., m = 1, 2 …, P and n = 1, 2 …., Q. Then, the MSE and RMSE can be defined as

$$\text{MSE} = \sum_{x=1}^{M} \sum_{y=1}^{N} \frac{[i'(x,y) - i(x,y)]^2}{MN} \quad \text{---------------------- (1)}$$

$$\text{RMSE} = \sqrt{MSE} \quad \text{---------------------------------- (2)}$$

Second image quality measurement parameter is PSNR. PSNR is deceases as RMSE increases and its unit is db (decibels). It is mathematically defined by

$$\text{PSNR} = 20\log_{10}\left[\frac{255}{RMSE}\right] \text{ db} \quad \text{----------------------------- (3)}$$

Maximum Pixel Value is 255 for an 8 bits/gray-scale image. All the possible combinations are having MATLAB codes. For measuring an objective change between two images PSNR uses a standard mathematical model. It assesses the image quality by comparing recreated image and the original image. Recreated images having lesser MSE and greater PSNR values are desirable.

Another parameter for a filter is *execution Time* (ET). ET means the time required to execute the complete filtering algorithm assuming that other software with the exception of operating system (OS) are running on it. A filter having lesser ET value is better as compare to a filter with greater ET value if all other performance-measureing parameters are alike (*Barten, 1999; Marta et al., 2003*).

Various Noise considered for Denoising

Medical images are received mostly from MRI, CT, and X-ray equipment. (*Ayush Dogra et. al. 2016*) By considering the appearance, mechanisms, noise types and origin of noise, image denoising method can be designed. *(Geoff Dougherty et. al. 2009)* They are categorised into different types depending upon their characteristics and source. Noise is always exist in images to some amount. All imaging machines are operated for a finite duration and so it becomes a source of stochastic noise as photons randomly arrives.

Optical imperfections and instrumentation noise (e.g. semiconductor devices' thermal noise) can cause add more noise. Aliasing of high-frequency signal components causes noise, and also quantization error is caused due to digitization. Other noise can get introduced because of communication errors and compression *(Dougherty et al., 2009; Diwakar et al., 2018*; *Goyal et al., 2018*; *Kadam et al., 2017).*

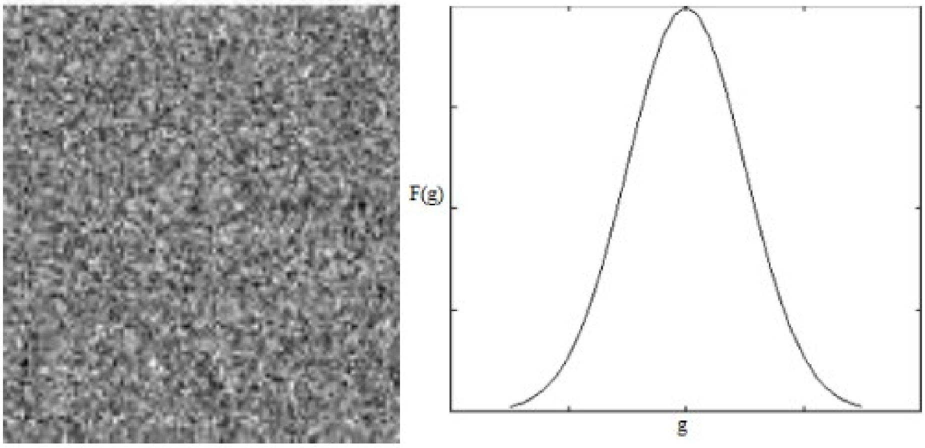
Gaussian Noise

Gaussian noise is found in almost all types of images (*Goyal et. al., 2018*). It spreads over the complete image. So, the pixel value of the corrupted pictures is the summation of the actual pixel value and Gaussian distribution (*Mohan et. al., 2014*). Its noise distribution shape is like a bell and expressed as:

$$F(g) = \frac{1}{\sqrt{2\Pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} \quad \text{……….. (4)}$$

Where, g - gray level of the pixel
m - mean value
σ - the standard deviation of the noisy image

The image having Gaussian noise with zero mean and 0.05variance is as shown in Fig. 1(a) and its corresponding Gaussian distribution is shown in Figure 1 (b).

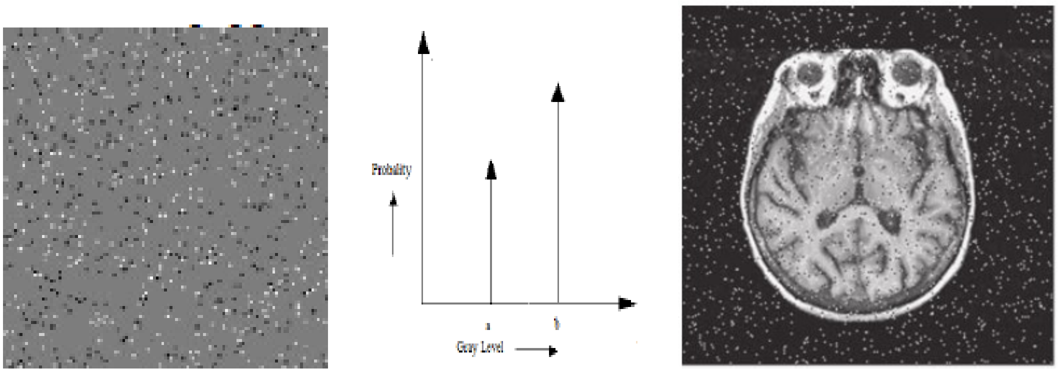


(a) (b)

Figure 1. (a) Gaussian Noise Image (b) Gaussian Noise Distribution

Salt and Pepper (Impulse) Noise

This noise is impulse type and termed as intensity spikes noise. The transmission channel is the place of its generation. It is having small black and white dots. Minimum intensity pixel value are black dots while maximum intensity pixel value are white dots. It is also named as salt and pepper noise. It's generated largely because of fault in the camera sensors, inappropriate pixel components, and wrong memory position. Figure 2 shows the look of the salt and pepper noise.



(a) (b) (c)

Figure 2. Salt and Pepper Noise

Periodic Noise

It includes periodic noise, Brownian noise, Speckle noise, White noise and Shot noise. Source of generation of these noise are different. Periodic noise is generated due to electrical interference. It usually arises while acquiring image, mainly if a strong mains power signal is present. It is space dependent and normally sinusoidal in nature with a multiples of a particular frequency. In the frequency domain, it is known as conjugate spots pair *(Marta et al., 2003*).

White Noise

It is having a constant power spectrum, i.e. its power spectral density is constant with frequency. It is like a white light, which covers almost all visible spectrum frequencies in equal amounts. It is totally uncorrelated, i.e. each pixel value is not related to its neighbouring pixel values. So its autocorrelation function is zero. Noise like normal distribution which have a continuous distribution, can also be white.

Coloured (Brownian) Noise

It is also known as Pink noise, 1/f noise or flicker noise. By integrating white noise, brown noise can be produced. It is the non-stationary stochastic process *(Dougherty et al., 2009; Kadam et al., 2017).*

Shot Noise (Photon or Quantum Noise)

Electromagnetic waves like visible light, x-rays and γ-rays have statistical nature which generates shot noise. As packets of energy and photons, these rays are emitted. Shot noise has Poisson distribution, a probability distribution. It is having $\sqrt{N}$ as average level, where N is the signal average. When N is very high, the SNR is very high as well, and any fluctuations in N due to other causes are expected to dominate over shot noise *(Dougherty et al., 2009).*

Speckle (Multiplicative) Noise

In an image Gaussian noise and speckle noise appear superficially. But, they are a generated due to different practises. So, they need different methods for their elimination. When an image, f (x, y), is corrupted by speckle noise then

$$g(x,y) = f(x,y)*n(x,y) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

It is also called as multiplicative noise. *(Geoff Dougherty et. al. 2009) Chaitali Kadam et. al. 2017)* Presence of speckle noise degrade ultrasound imaging which reduces contrast (*IntechOpen Book Series, 2013*).

Rician Noise

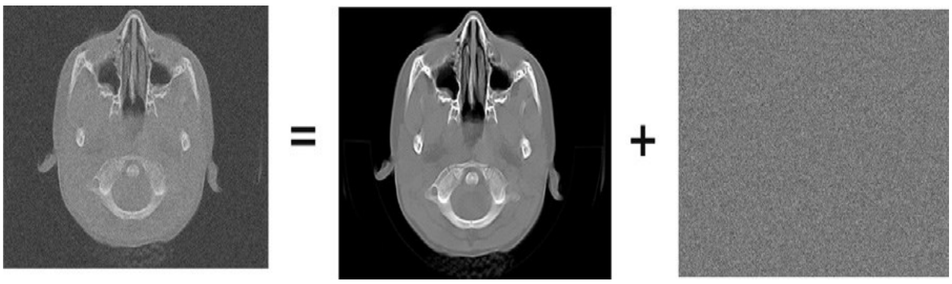
Noisy magnitude MR image intensity follows the Rician distribution. Because of the noise, low signal intensities i.e. SNR less than 2 are influenced. The nature of phase images noise are also studied and compared with magnitude images. They are found to be quite different from each other. But, In both the cases the distributions of noise pattern are almost Gaussian for SNR > 2 *(Gudbjartsson et al., 1995).*

Rayleigh Noise

Rician noise, Gaussian Noise and Rayleigh noise are mainly present in MRI images. For MR images, if value of SNR is more than 2 then Rician distribution gets converted into Gaussian noise distribution. And SNR converges to Rayleigh distribution, if SNR value is close to zero. Although for the elimination of Rician Noise, research work is available in abundance. Still the literature for the elimination of Gaussian and Rayleigh noise from MRI images is scarcely available. (*Goyal et al., 2018*)

Classification of Denoising Methods

Image denoising is to find a clear image from a corrupted image (*Goyal et al., 2018*). The addition of true image and a noise constituent forms the noisy image, as shown in Fig. 3. Without prior information, it becomes difficult to denoise the image successfully.



Noisy Image = Clean Image + Noise

Figure 3. Formation of Noisy Image

Human visual system can easily identify the structures, even if there is substantial amount of noise. If image have small SNR or low contrast, it becomes very difficult to identify anatomical structures. Denoising methods are classified in 2 sets: *acquisition based noise reduction* methods and *post – acquisition image denoising*. In the first set, the data acquired many times and then their average is taken. So, it require more time for acquisition. In second set, the method to reduce noise from the images is to use the post processing methods. But, In first approach the acquisition time is less because of restrictions such as patient comfort. Consequently, In most applications, the SNR value have a practical limitation e.g. MRI data. So, post - acquisition image denoising approach is a low-cost and impressive approach (*Mohan et al., 2014*).

The aim of image noise reduction is not only to denoise but also to protect the clinical details. The key tests for denoising the image are (*Diwakar et al., 2018*):

- Flat areas should remain flat.
- To protect the image borders (no blurring).
- To preserve the texture information.
- To preserve total contrast.
- To avoid new artefacts.

The noise reduction methods classified based on denoising approaches are (i) filtering method, (ii) transform domain method iii) statistical method and iv) Machine Learning (ML) Methods. In filtering method, the linear or non-linear filters are used to eliminate the noise. Transform domain method includes the transforms like Fourier Transform (FT), Wavelet transform (WT), Curvelet transform (CT) etc. to eliminate noise from images. In statistical method includes Maximum likelihood approach, linear minimum mean square error (LMMSE) estimation etc. estimate noise from MRI. (*Mohan et al., 2014*) In ML approach the study and structure of algorithms are explored. It can learn and make forecasts from the information. e.g. *Artificial neural network (ANN), Support vector machine (SVM)* etc. (*Mohan et al., 2014*; *Perona et. al., 1990*)

Filtering Methods

It is a conventional technique to eliminate or decrease noise. It is also called as spatial filtering. It denoise the images by using filter directly on corrupted image. It is again divided into linear and non-linear filtering types.

Spatial and Temporal filter

To eliminate Gaussian noise from MR images, the spatial filter and temporal filter are used. In spatial filtering the filtering processes are executed directly on the pixels of an image. Here, an image and a spatial filter are convolved. This method decreases the variance of the image. But, sharp edges get blurs. As noise and the signal are reduced by the equal amount so the frequency dependent signal-to-noise ratio remain unchanged.
Similarly temporal filtering (executed on a series of images) will blur the series and smoothing out the temporal changes. Temporal filters also requisite to adjust their features to the motions in the image series and should be able to handle various pixels accordingly. A narrow frequency response temporal filter blurs the edges while noise gets added due to aliasing in filter having wide frequency response. (*J. Mohan et. al. 2014*) (*Ali M. Reza 2013*) (*E. R. McVeeigh et al 1985)*

Anisotropic Diffusion filter

Diffusion means the spread of particles through random motion from areas of higher concentration to areas of lower concentration. And Anisotropic refers to the direction applied. Thus, anisotropic diffusion filter is a multi-scale averaging and edge finding system. This overpowers the disadvantage of spatial filtering and significantly increase the quality of image while protecting the image boundaries, effectively eradicating noise in homogeneous areas and edge refining. Diffusion centred algorithms include simple, local, similar calculations over the complete image. It is built on second order partial differential equation (PDE) in an anisotropic environment. Smoothening is framed as a diffusive method, and by choosing the local gradient intensity in various directions smoothing is repressed or blocked at borders (*Mohan et al., 2014*; *Perona et al., 1990*).

Nonlocal Means filter

It is an algorithm used for decreasing the noise from images. Here "local mean" filters takes the average value of a set of pixels neighbouring to desired pixel. It smooths the image. While In non-local means filter an average of complete pixels of the image is calculated and then the alikeness between these pixels to the desired pixel is computed. It gives much better clarity and makes less damage to the details (*Diwakar et. al., 2018*; *Mohan et al., 2014*; *Buades et al., 2005*).

Combination of Domain and Range filtering Techniques

Tomasi et al. (1998) suggested the bilateral filter. It is a non-iterative alternative to anisotropic diffusion filter. In both methods, edges are preserved while images are smoothed. But, bilateral filter method does not include the PDE solution and executed in a one loop. It has domain and range filters, both are Gaussian filters. In domain filter the coefficients are relative to the spatial distance (geometric) of target pixel and its neighbouring pixel. In range filter the coefficients are relative to the photometric (intensity) distance between the target pixel and its vicinity. Output of the both filters gives the final image.

Transform Domain Approach

Transform-domain filtering like FT and WT convert the spatial realm data to the frequency realm. And filtering operations are executed in frequency realm. Later, by using inverse transform filtered frequency representations are converted back to the spatial realm. The filtering methods in the transform realm are modulus maxima method denoising, thresholding denoising, and Translation Invariant Wavelet Denoising. In the first method, initially image's singular point is detected. The modulus maxima on the singularities of the required data and noise in the WT are not same. Second approach i.e.the thresholding technique is having different methods like Soft and Hard Fixed Threshold, Adaptive Threshold etc. In thresholding methods, threshold is fixed on the noise variance. Comparing the hard and soft thresholding methods, the hard threshold can give better edge preservation, but the image is susceptible to problems like ringing, pseudo-Gibbs phenomenon. The soft threshold technique is having smoothening property, but has the weakness of edge blurring problem.

Third approach i.e. Translation invariant wavelet noise reduction technique is a development founded on the thresholding process. In this technique, on the corrupted data cycle translation is performed n times and then Wavelet Denoising threshold technique is executed to denoise the data and then the results of de-noising are averaged. In these noise reduction approaches, the threshold technique was used more extensively because it is simple to apply and easy to compute. But, the appropriate selection of threshold technique depends on the situations, and it is still one of the directions for further research (*Zou et al. 2015*).

Curvelet Transform

The WT centered noise reduction approaches are not appropriate for the data having edges. To resolve these difficulties and to identify, represent and to do operations on high dimensional data, Curvelet transform is used. It have directionality and anisotropy property to reflect the edge directions in the image (*Mohan et. al., 2014*) For image denoising the Curvelet transform is firstly used by Starck et al. *(2002).* Below steps are followed in the image noise reduction algorithm are:

1. Calculate all thresholds for curvelets.
2. Calculate norm of curvelets.
3. Process noisy image by curvelet transform.
4. Apply hard thresholding on the coefficients of curvelet.
5. Perform inverse CT.

The Curvelet reconstructions shows greater visual class as compare to wavelet-based reconstructions, present visibly sharp images and, especially greater class regaining of edges, weak linear and curvilinear structures. According to the concept for Curvelet and Ridgelet transforms, these novel methods beat wavelet approaches in few image reconstruction difficulties *(Starck et. al. 2002; Candès et al., 1999*)

Contourlet Transform

Images having smooth areas which are separated with edges, the wavelet transform is very useful technique. But, if the edges are having smooth curves then it cannot work properly. The contourlets are capable of seizing contours and small parts in images. Minh N. Do & Martin Vetterli proposed a Contourlet transform which have discrete filter bank of specific linking with the allied continuous-domain contourlet expansion. The linking is demarcated by a directional multiresolution scrutiny which offers continuous alterations at both spatial and directional resolution. It achieve the optimal approximation rate.

The stages for denoising the images using contourlet transform are: 1. Perform contourlet transform to decompose the image and find the scales and directions number. 2. Perform thresholding on countourlet wavelet in every direction and in every scale. 3. Perform inverse contourlet transform to recreate the noise free image (*Do et. al,. 2005*).

Fourier Transform

Duan et al. (2016) suggested a method built on second order total generalized variation mode to denoise images. Here, FFT-centred split Bregman algorithm was used to give the high computing effectiveness. It was detected that this arrangement denoise the images better than other denoising approaches. It decreases noise efficiently without producing staircase effects. But, it loses minor structural characteristics in the image.

Wavelet Transform

Wavelets transform are mathematical functions like Fourier transform. It divides signal or images into various frequency constituents. These frequency constituents can be attained by wavelets with a resolution matched to given data scale. Normally, a wavelet centred denoising method contains the following stages: 1. Image is converted into wavelet realm and obtain the coefficients of wavelet. 2. The wavelet coefficients are processed. It contains the processes like thresholding to reduce the noise in the wavelet realm. 3. To produce the denoised image, find inverse wavelet transform of the modified coefficients. These steps can be continued for a number of times depending upon scale and degree wavelet decomposition (*Mohan et al., 2014*).

Threshold Estimation

The image noise holds very less value and rooted with clear pixel value which form a corrupted pixel. One of the approaches to pixel denoising is thresholding. Here, wavelet coefficients having small values are discarded from high frequency bands while wavelet coefficients having large values are kept. The scheme to find value to distinguish lesser and higher wavelet coefficients is called as threshold estimation. SureShrink is a thresholding system proposed by *Luisier et al.* (2007) which apply a subband adaptive threshold. Here, for every subband centred on Steins unbiased risk estimator (SURE) is used to calculate a distinct threshold. While BayesShrink (*Luisier et al.,* 2007) is used by a Bayesian mathematical framework. For the wavelet coefficients, it takes a generalized Gaussian distribution in each subband to compute the threshold.

Shrinkage Rules

The shrinkage rule describes the threshold process. Here, each coefficient of wavelet transform field is equated to a threshold value. In hard threshold, if coefficients are smaller than the threshold then they are replaced by zero. It can create artifacts in the recreated image. While In the soft thresholding recreated image may get oversmooth. Like Hard threshold even In Soft threshold, the process of replacing the lesser coefficient by zero. but the remaining coefficients are substituted by deducting threshold values. For visual appearance of images, soft thresholding is found to give better result than hard threshold (*Diwakar et al., 2018*). *Xiao et. al. (2011)* compared the characteristics of numerous thresholding methods based on wavelets for denoising on the basis of PSNR. e.g. VisuShrink, SureShrink, BayesShrink, Feature Adaptive Shrinkage.

To overcome limitations of hard and soft thresholding, an optimal linear interpolation (OLI) shrink algorithm (*Jansen et al., 2011*) is suggested for thresholding. It suggests a statistically optimum adaptive wavelet packet thresholding function which is built on the generalized Gaussian distribution. Zhang et al. *(2019)* proposed another wavelet threshold method which gives better results than existing hard threshold and soft threshold de-noising approaches, with respect to objective and subjective visual effects. Also, *Golilarz et al. (2020)* proposed improved adaptive generalized Gaussian distributed oriented threshold function (improved AGGD) for the MR images to increase the outcomes of the adaptive soft and hard threshold functions. It gave results which are quite compatible with the existing methods like adaptive threshold, standard threshold etc.

Statistical Approach

Noise present in magnitude magnetic resonance (MR) images is generally modelled with the help of a Rician distribution. Few research works on denoising methods built on statistics/estimation approaches have been reported in the research field for MR images. Estimating the noise variance of MR images is an essential stage for denoising because of several reasons. One main reason is, it offers a quality measure of the MR data which is useful for measuring the SNR and also for the MRI structure study, this noise variance is useful. Lastly, it's an essential factor in noise removal, segmentation and registration of images. (*J. Mohan et. al. 2014*)

Maximum Likelihood Approach

For low SNR, the noise in MR magnitude images observes a Rician distribution which is data-reliant. The random variations and bias introduced due to Rician noise is hard to eradicate. (*He et. al., 2009*) For reducing bias, *Sijbers et al. (2004*) assessed the Rician noise level and did image recreation using maximum likelihood (ML) method. While nonlocal maximum likelihood (NLML) estimation technique gives an optimum estimation result which is more accurate. (*He et. al., 2009*) Mustapha Bouhrara et al. (*2017*) proposed multispectral addition to the nonlocal maximum likelihood filter (NLML). It combines both spatial and spectral data to do effective denoising.

Linear Minimum Mean Square Error (LMMSE) Estimation

To estimate the Rician noise, *Aja-Fernandez et al. (2008)* suggested the LMMSE method. It takes the sample distribution data of local statistics of the input data like local variance, the local mean and the local mean square value. Here, each corrupted pixel's real value is evaluated by pixel set chosen from its neighbourhood. For the removal of Rician noise from 3D MRI, *Golshan and Hasanzadeh (2011)* have proposed a nonlocal treatment of the LMMSE technique. In this technique, the hard threshold value of controlling factor is used. Then, *Golshan et al. (2013)*improved this by altering the controlling factor as per the noise level.

Phase Error Estimation (PEE)

Tisdall and Atkins (2005) suggested the PEE method for MR Image noise reduction. It overcomes the disadvantages of Wavelet transform based algorithms having the danger of smoothing fine details much more than required, especially for images having very low SNR. The proposed solution is a novel system built on iteratively using a successive non-linear filters. Every filter is applied to change the estimate into larger arrangement with one part of acquaintance about the difficulty, till a steady estimate is attained. It needs moderate computing power and works properly on inversion recovery images.

Non-parametric Estimation Method

Awate and Whitaker (2005) suggested the non-parametric neighborhood statistics technique for decreasing the noise content in MR images. Here, images are modelled as random fields. Reduction is used together with the Rician noise model. This model is used like a tool to retrieve higher-order statistics of image neighborhoods from corrupted data. It deconvolves the noisy input data with the noisy statistics. Later, these statistics are used as priors within an optimal Bayesian noise reduction background. *Awate and Whitaker (2007)* used non-parametric empirical Bayes (EB) method for feature protection noise reduction of MR images. It bootstraps itself by assuming the prior, i.e., the noise free image statistics of the corrupted input and the information of the Rician noise model. It is based on concept of EB estimation.

The prior is modelled by it in a non-parametric Markov random field background by enhancing an information-theoretic metric. The simplification and authority of non-parametric modelling, joined with the new EB arrangement for prior assessment. It confirms that the suggested technique evades enforcing ad hoc prior models for noise reduction. So, it creates noise reduced images that protect the vital features like edges corners, boundaries etc. This method have a low RMSE.

Machine Learning (ML) Approaches

The study of computer algorithms which have the property of self-learning and enhance itself repeatedly through training and by the use of data is the Machine learning (ML). It is considered as an artificial intelligence branch. These methods are quite effective in image-based analysis, sickness recognition and sickness prediction. To reduce the reliance on machinist and to have precise diagnose, Computer Aided Diagnosis (CAD) system is an main and useful method for diagnosing breast tumour recognition and classification, foetal growth and development, brain working, skin lesions and lungs infections.

In many applications, the machine learning methods are found to be better than other medical image noise reduction practices. The machine learning means are preferred for MRI, ultrasound (US), X-Ray and Skin lesion images, due to fast and computational results. These methods help to reduce time, economic and give speedy result. (*Kaur et al., 2018*) ML topics includes linear models, learning with kernels, clustering analysis and dimensionality reduction etc. *(LeCun, et al., 2015)* ML approaches are conventionally divided into three groups, based on the input type or experience received by the learning system:

> *Supervised learning:* It inspects the data for training and gives an inferred function which assist for solving new problems. E.g. Scalar Vector Machine (SVM), linear regression etc. Unsupervised learning: Labels are not specified to the learning algorithm and it discovers structure of itself from the given data. It discovers hidden patterns in the given data or help for finding the hidden feature. E.g. Neural network like autoencoders, generative adversarial networks (GANs) etc. Reinforcement learning: It is built on the concept of compensating the desired activities and/or penalising the undesired ones. It means, a reinforcement learning manager is capable to observe and understand its atmosphere, take actions and learn by trial and error method. e.g. Q-learning, Deep Q Network (DQN) etc. (*Xiao et al., 2011;Bengio et al., 2013; LeCun, et al., 2015).*
>
> *Other ML Approaches:* Dimensionality reduction and Deep learning (also called as deep structured learning) belongs to broader part of machine learning methods. Dimensionality reduction means the method of decreasing the total number of features of data and guarding the variation in the original dataset as much as possible. It is a data pre-processing step i.e. Dimensionality reduction is performed before training the model. e.g. Principal Component Analysis (PCA), Singular Value Decomposition (SVD) etc. *(LeCun, Y et. al. 2015)* Deep-learning architectures includes deep neural networks, deep belief networks etc. For Medical image analysis, these deep learning architecture give results equivalent to and in some cases superior than professional's results *(Wang et al., 2015).*

Supervised Learning

Gondara (2016) proposed medical image noise reduction method by using convolutional denoising autoencoders. Here higher noise is well inhibited and edges are neat where other noise reduction denoising methods mostly would get flail. Heterogeneous images combined to enhance sample size. Simplest of networks reconstructed images with high noise levels. Here, training samples as few as 300 are enough for good performance. *Elhoseny et al. (2019)* suggested optimal bilateral filter and Convolutional Neural Network to attain higher PSNR. Noisy images are classified as normal or abnormal by Convolutional based Neural Network (CNN) as a classifier.

Unsupervised Learning

A cluster centred dictionary learning method can be used along with wavelet transform. *Ghadrdan et al.* (*2014*) suggested a novel system founded on wavelet transform. Here, noise reduction was attained with the help of clustering and dictionary learning. In this method, the best features was preserved with the help of wavelet and clustering in the CT images. Noise level estimation of a particular image was calculated to acquint the cluster by perceiving greater PSNRs. Because of clustering and dictionary learning, the edges are properly protected even if the image is high textured. Its speciality is to denoise the image and still protecting the minor features and geometrical arrangements. The complete process does not require to set the parameters manually. *Rai et al. (2021)* experimented on MRI/CT datasets which run on a GPU-built supercomputer. The proposed algorithm conserves the important data of the images and also increases the pictorial value of the images.

Other ML Approach

For low dose CT image noise reduction, *Zheng et al. (2013)* suggested a novel technique with Pointwise Fractal Dimension. Here an altered Pointwise fractal dimension (PWFD) function was executed for computing value of weight of every pixel by applying Non-local means (NLM). The function was again executed to compute the variance from the two equivalent windows to assess the necessary weights. This technique provided good quality noise free images having sharp and smooth features, but it may drop minor details. *Kang et al. (2016)* suggested a deeper type of convolutional neural network (CNN) and WT.

Here, the restoration differences decreased by limited angle tomography along with filtered back projection. *Chen et al. (2017)* suggested a technique for CT image noise reduction with the help of deconvolution network and shortcut links in a CNN model. Here links is considered as a residual encoder decoder convolutional neural network (RED-CNN). Here, a patch centred training is executed for preserving the edges. *Patil et al. (2021)* proposed a combination of WT and Singular Value Decomposition (SVD) for medical image denoising. WT is having inherent property of denoising while SVD is having dimension reduction property which helps to reduce the noise present in image.

Comparison of Denoising Techniques

For comparing denoising techniques, the outcomes of few current prevalent approaches are studied with respect to two aspects: (i) visual scrutiny, (ii) evaluation metrics. To measure the visual scrutiny, mathematical or precise process is not available. But, normally four norms are observed for better visual scrutiny,: (i) artifacts visibility; (ii) protection of edge particulars; (iii) low contrast objects visibility and (iv) texture protection. Evaluation metrics like RMSE and PSNR standard are considered for measuring the correctness of image denoising approaches (*Diwakar et al., 2018*).

Table 1. Comparison Table for RMSE

Sr. No.	Denoising Method	Image corrupted by Gaussian Noise, ó			
		10	20	30	40
1	Neural Network (CNN) (*Chen et al. 2017)*	7.1501	17.6313	27.2951	37.2791
2	Autoencoder (ANN) (*Gondara 2016)*	7.2341	17.1903	27.1078	38.2351
3	CNN and Wavelet (*Kang et al. 2016)*	7.9201	17.1245	27.1091	37.7812
4	Non-local means (*Zheng et al. 2013)*	7.4668	17.4150	27.4157	37.3013
5	Frequency Domain (FTT) (*Duan 2016)*	8.1727	18.1708	28.0817	37.9911

Table 2. Comparison Table for PSNR

Sr. No.	Denoising Method	Image corrupted by Gaussian Noise, ó			
		10	20	30	40
1	Neural Network (CNN) (*Chen et al. 2017)*	30.4621	23.9812	19.2312	16.1235
2	Autoencoder (ANN) (*Gondara 2016)*	30.3091	22.1094	18.3467	16.0912
3	CNN and Wavelet (*Kang et al. 2016)*	30.2136	23.1238	19.1290	16.4562
4	Non-local means (*Zheng et al. 2013)*	30.6353	23.2813	19.3408	16.6642
5	Frequency Domain (FTT) (*Duan 2016)*	29.8509	22.9115	19.1317	16.5074

Table 3. Advantages and Disadvantages of Denoising Methods

Sr. No.	**Denoising Method**	**Advantages**	**Disadvantages**
1	Neural Network (CNN) (ML) (*Chen et al. 2017)*	Even by using small training dataset good SNR can be attained.	For small sample denoising its difficult to obtain an optimum design.
2	Autoencoder (ANN) (ML) (*Gondara 2016)*	Abundant prospective of deep learning for noise reduction, structural protection, and lesion recognition at a high computing speed.	Need more time and memory space for computation.
3	CNN and Wavelet (ML and Transform Domain) (*Kang et al. 2016)*	Combination of deep convolution neural network and directional wavelet.	Need more time and memory space for computation.
4	Non-local means (Spatial Domain) (*Zheng et al. 2013)*	Images are sharp and smooth.	Execution time is more. Minor constructions are assumed as noise and hence eliminated.
5	Frequency Domain (FTT) (*Duan 2016)*	Computationally efficienct due to the explicit FFT-based split Bregman algorithm. Denoise effectively and cause no staircase effects.	Lose structural features fine details.

Conclusion

Medical imaging has developed as an important part of medical sciences. So, exact and accuracy of images are highly desirable for quick and timely diagnosis. Hence, for designing an image noise reduction algorithm, one has to be aware about the prior knowledge about the corruption present in the images. This paper explores noise models and contains detail literature survey of various denoising approaches and techniques. Desired features and difficulties of noise reduction algorithms are mentioned. Besides this, it describes the common tools used to assess the denoising algorithms performance.

The ultimate goal of researcher is to have a universal denoising algorithm. Yet there is no universal denoising technique. The noise free outputs of the suggested algorithms and prevailing algorithms are compared with the help the assessment approaches mentioned above. Medical image noise reduction methods and comparative analysis based on evaluation parameters metrics like PSNR, RMSE etc. are also studied.

It is clearly visible that any single image noise reduction method is not able to cover all advantages with respect to denoise, edge protection, robustness, user friendly, relevance to the various the acquisition methods, and calculation price.

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