Critical Findings on Restoration of Magnetic Resonance Images

Sujeet More, Jimmy Singla

Abstract: The explosion of numerous medical images lead to the development of many different techniques to provide an accurate result. Although the signal to noise ratio (SNR), resolution and speed of magnetic resonance imaging technology have increased, still magnetic resonance images are affected by noise, contrast, and artifacts. To provide the image content or features relevant to diagnosis, contrast enhancement and reduction of noise with preservation of actual content should be carried out. The purpose of this paper is to present a critical review of different types of noises with an overview of diverse techniques for denoising and contrast enhancement for magnetic resonance images and discuss the advantages and limitations of these techniques with broad ideology.

Keywords: Denoise, Contrast enhancement, Magnetic resonance imaging, Image filtering, Gaussian noise.

I. INTRODUCTION

Magnetic Resonance Imaging is widely used in medical images for detailed diagnosis for interpretation of tissues and other underlying features. In general, X-rays are the most frequently used imaging type for the visualization and interpretation of hard tissue such as bone, while modalities such as magnetic resonance imaging, computed tomography, and ultrasound are used for the visualization and analysis of soft tissues in the human body. Despite having many pros of each of these modalities, each also has its respective cons. Specifically, the diagnosis and monitoring of several diseases are limited by numerous factors such as the contrast, brightness, or noise in the image. These factors degrade the performance of computer-aided diagnosis (CAD) systems [1] or lead to the misapprehension of tissues by doctors. Currently, the development of CAD systems using imaging data obtained from medical imaging modalities and image/pattern recognition techniques is progressing rapidly, and researchers are using medical imaging datasets to develop accurate and efficient methods to meet the current need for the diagnosis and detection of disease. Most computer-aided diagnosis systems include preprocessing as a major step before segmenting and classifying the images. Noises, uneven edges, stubby contrast, and other artifacts make more difficult for further steps involved in the diagnosis. The diagnosis of any disease depends on the quality of the image and features to be used. For proper interpretation of different tissues and other underlying features, quality of contrast is necessary.

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If the image is less enhanced, the performance of the system gets degraded due to the quality of the image. If the image is over enhanced, then the system can't distinguish the different features in the image. Though, many images acquired from magnetic resonance imaging exhibit an inadequate contrast that leads to weak tissue boundaries between different types of hard and soft tissues, contributing to difficulties with further quantifiable measurements like segmentation, classification, and analysis of the tissue structures. This leads to improper processing of further experimentation. Figure 1 shows different imaging types with their stubby contrast.

The perceptible quality of magnetic resonance images plays a very crucial role in the diagnosis of disease and that can be degraded by noise which exists in the image due to the acquisition process [2]. Noise is affected by instruments, transmission media, and different types of radiations. The noise affects both computer-aided diagnostic system and the analysis on the disease like feature selection, segmentation, and classification. Noise reduction in images is still a challenge for many researchers because noise reduction introduces the blurring of the image.
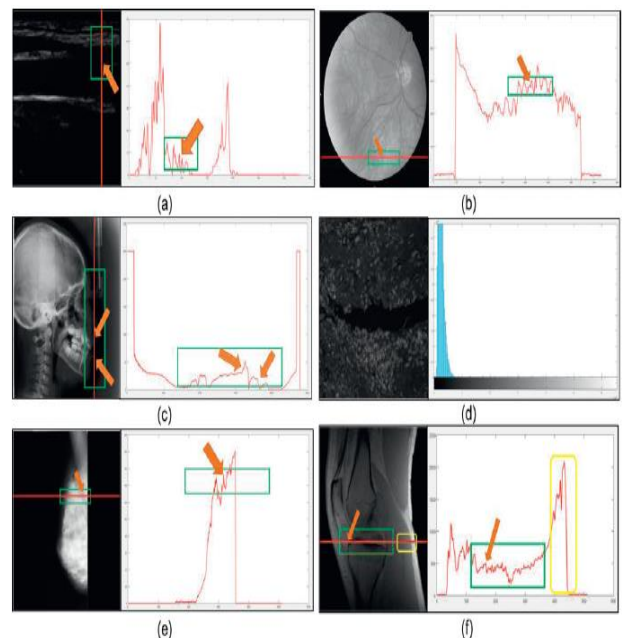

Fig 1: Contrast of different types of imaging. The first row consists of (a) and (b) Ultrasound and fundus image respectively. The second row consists of (c) and (d) X-ray and Fluorescent image respectively. The third row consists of (e) and (f) mammograms and MRI images respectively.

The rest of the paper is classified into different sections. Section 2 describes the literature review. In Section 3, different contrast enhancement techniques are discussed. Section 4 introduces the diverse types of denoising techniques. Section 5 describes the comparative analysis of denoising and contrast enhancement techniques. The conclusion and discussion are presented in Section 6.

II. LITERATURE REVIEW

Magnetic resonance images require enhancement for better visualization and to have precise results. The histogram equalization (HE) technique is best suited for these kinds of enhancement which reconstructs the brightness value of these images [3]. It scales the magnitudes of the probability density function of the original input image before applying histogram equalization. The scaling factor is adaptively adjusted according to the averaged image intensity values of the image. The AHE and CLAHE use contrast amplification for every neighboring pixel value. The CLAHE overcomes the drawback of AHE by reducing the amplification of noise. The BPDHE and RMSHE which produces lower entropy values than that of HE [4]. The RMSHE produces an irrelevant enhancement of the image, while BPDHE provides an unnatural look and doesn't prevent the washed-out image appearance.

To enhance the contrast of magnetic resonance images, the intensity level should be equally distributed. To equally distribute the intensities, the calculation of CDF [5] is required with CHE formula for generating new gray values for the image. The improvement of this method is QDHE which provides median calculation by partitioning smaller parts of histograms with maximum and minimum values of the intensities. Some researchers think this contrast enhancement as an optimization problem and produce an optimal solution using ABC algorithm [6] to evaluate the quality of the image. The transformation of image is utilized by generating new pixel intensities combing the fitness function. ABC algorithm is motivated by honey bees which provide a population-based search for food positions that are evaluated and adapted by artificial bees. ABC algorithm faces two challenges first is about transformation function and second is object evaluation. Existing HE methods are used to increase the contrast but suffer from contrast stretching problem [7]. The HE can't distribute the pixels uniformly within the range this causes the image to be unclear. The transformation is carried by a discrete wavelet transform function followed by a spatial domain.

Contrast enhancement with local gray level transformation using S-curve for improving the contrast with noise elimination [8]. This local gray level transformation is done with k X k non-overlapping blocks with a reduction of intensities. The global transformation leads to over contrast but blocking of artifacts in some cases. If there is an increase in the number of blocks that also effects the contrast of an image, so the block size of the optimum number is to be selected for an accurate and effective resultant image. New image enhancement with automatic adjustment of contrast is introduced [9] which works with some images of brain MRI. This AIR-AHE method applies partial contrast stretching by saturating the upper and lower parts of the image by 1% and calculates the maximum intensity of the image. The WMH regions are segmented using hierarchical and mathematical operations.

A novel optimized contrast and edge enhancement technique, [10] introduced with fitness function to achieve a resultant clear image. This method calculates the histogram of the image then applies the fitness function for the optimization technique. This optimization technique automatically adjusts the plateau limit for clipping and transforms the image based on expanded CDF. The proposed method has slow computation time but provides accurate and best results for low contrast images. The global transform can yield to varying characteristics of the image which gives very poor precision in some parts of the image, so region-based technique [11] can improve the performance. A seed is selected and the image is divided into foreground and background, the foreground region is applied with AHE and then the background is added to the foreground with gradient. The modified discrete wavelet transform [12] for better appearance of the low enhanced brain MRI. The T1-weighted MRI slices are applied over HE and with DWT the image is divided based on a low and high frequency. The DWT doesn't create unwanted artifacts and preserves the edges of the tissues in the image.

A mathematical model is proposed to estimate the noise in the image using fuzzy logic [13]. The degree of fuzziness is used to measure the noise in the image. The gray level of the particular pixel is assigned as the membership value of that pixel. The proposed method produces a coefficient of prediction with a high goodness of fit and the noise variance which differs from an actual value. This model helps to find the depth level of smoothing. The Rician noise in magnetic resonance images has to be removed utilizing non- local pixels. The method traces out the pixel, if it is in the smooth area then the search window will be small, if the pixel is in non- smooth area then the search window will be large and the mean is estimated with a modified MAD estimator. Denoising is the foremost thing to be carried before segmentation [14], using different types of images like CT scan, MRI and PET. In the paper, a detailed survey of different types of noises, its parameters and different methods applied for image denoising is discussed. This issue of denoising can be resolved by the wavelet-based method [15]. The liver MRI is decomposed into a set of functions then the corresponding wavelet signals are used for sampling. This method will help to solve the problem of Gaussian, salt and pepper and impulse noises. [16] discusses the pros and cons of diverse available techniques for denoising the corrupted images. Here the SAR image denoising, adaptive edge-preserving, sparsity residual, local and non- local means techniques are discussed. The survey elaborates, few filters work good for particular type of the image, not all filters are good. The deep learning is the fast-growing field, with this denoising is performed on small sample size [17]. The intervals are considered for experimentation to find peak- to signal ratio, SSIM, and NMI. The neural network used is feed-forward that integrates residual learning to boost the training process.

The high capacity of the neural network is due to the number of layers in deep architecture and flexibility to understand the characteristics of the image along with small intervals to denoise the image. The sparse tensors [18] for denoising the MRI is an improved method. To efficiently compute the process an improved scheme is proposed which operates on different types of variables. The image is reshaped and convergence analysis for brain flair images. This proposed method preserves the structural relations between the magnetic resonance image series. A filtering technique based on distance algorithm [19] is proposed with a cumulative distribution function of different pixels and compared the similarities with different acquisition parameters. Similar pixel values are fused to produce the resultant output then the method is compared with local and non- local methods, but the computational time is more compared to other techniques. Non- local means [20] techniques perform a better response to the denoising problem. NLM filter is best for preserving the edges while denoising. The NLM is classified into Fast NLM, Adaptive NLM, Transform domain NLM and Statistical based NLM. Reducing the cost of computation and removing the excessive noise of Gaussian noise where weights are computed and neighbor pixels are optimized. Block classification is applied to the singular value that performs decomposition and checks the dominant edges in every single block. The multiresolution framework can be efficiently applied over spatial frequency by combining domain transformation. To reduce the processing time patch distance computation is combined with DCT. Comparative analysis on T1- weighted and T2- weighted brain MRI for Rician noise to find maximum accuracy is carried out and a combination of loss correlation and contrast distortion parameters are estimated. To protect the data with structural constraints like edges, surfaces, and quality of the image-enhancing PSNR value is an inventive technique that works on optimization criteria. The DF, MFF and CNN filters are used to categorize the denoised image. The spatial and gaussian parameters are estimated by hybrid optimization [21] along with the bilateral filter. The CNN classifier categorizes the image as class 0 and class 1. The 10- fold cross-validation is deployed for the experimentation of the denoising technique to estimate RMSE and SSIM. BM3D is used instead of thresholding, where the value is automatically set for data and noise parameters. A combined effect of VST and block matching is used to perform denoising aligned with CLAHE for enhancement of the quality of an image. An accurate resultant for reduction of noise using the averaging method. The efficient NLM computational method for denoising a larger magnetic resonance image with the block method is used for precise results. An assumption is made before study with a weighted average of all the pixels in the image, and the distance is estimated between neighboring pixels using a mathematical equation. Adaptive techniques for estimation of noise in magnetic resonance images is perceived by tensor approximation and iterative technique for MRI. The evaluation of performance parameters for PNSR, SSIM, and FSIM is made for T1- weighted, T2- weighted and PD- weighted images. The method outperforms with improvement in PSNR value. Digital Signal Processing helps

to build an advantageous area with avoiding noise and signal in the image. SWT method decomposes the redundant wavelet from DWT. SWT, is mainly used for brain image processing with the removal of noise with enhancement in the quality of the image. The hybrid adaptive DWT is implemented for corrupted images with various noises. The method calculated the independent components of the image with a random weight vector and decomposes with DWT where the threshold is applied for each of the components with non- linear function. Once a matrix is generated then the cross matrix is performed and MSSIM and SSIM parameters are estimated. Weighted image with diffusion is effective in treating the noise from the image. The method extracts some features from the images which have structural correlation and high SNR value. The TV and BM3D methods are less performed methods when compared with DWI. The deep architecture of DWI is efficient for increasing the capacity and flexibility of image characteristics. Deep Learning is an emerging field of Artificial Intelligence. The noise in the image can be reduced using deep learning method. The appearance of the image, quantitative measures and qualitative measures outperform than any other method. Each filter has different weights with cross-subject and cross-regional features. Cross-regional makes robust to noise with patterns of high- frequency bands. The model is fully capable of reducing the artifacts and noises from the image.

III.   CONTRAST ENHANCEMENT TECHNIQUES

The continues improvements in the magnetic resonance imagining system still makes it vulnerable to many kinds of problems like uncertainty in visual quality of radiographs. Unlike still images, MRI has complex structures and different modalities. So, analyzing and processing these images require superior models to have detailed information and prevent data loss. There are many algorithms researchers have designed to enhance the image.

A.   *Histogram Equalization (HE)*

It is a method that improves the contrast of the image. This equalization has a transformation function known as CDF. The intensity of a pixel is represented by i and the available intensities are $0 \leq i \leq L-1$ where L for an 8-bit image would be 256, the available intensities are in that case 0 to 255. An intensity (i) value of L-1 is considered as white and an i value of 0 is considered black. It would be good to have a function that based on the intensity value in a pixel and how many times that intensity value occurs assign a new intensity value to this pixel, this function is declared T(i).

$$s = (i), 0 \leq i \leq L-1 \qquad (1)$$

The value s is the new pixel value based on the old pixel value. It is now clear that histogram equalization manipulates data. The intensity values in an image can be regarded as random variables that can have any value between 0 and L-1. This random event has a so called cumulative distribution function (CDF) associated to itself. This function describes the likelihood that the random variable will be assigned a value less or equal to a specific value.

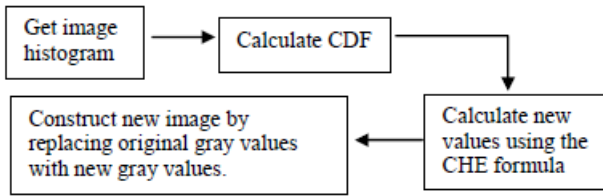### B. Cumulative Histogram Equalization (CHE)

Fig 2: Stages in CHE

The CHE described in figure 2, produces the enhanced image by calculating the CDF and these new values are provided to the CHE equation. The enhanced image is produced by replacing original pixel values with new estimated pixel values. Equation 2 provides CDF calculation,

$$CDF\ (k) = \sum_{i=0}^{k} Pr(ri) \quad k = 0,1,2, \ldots, L-1 \qquad (2)$$

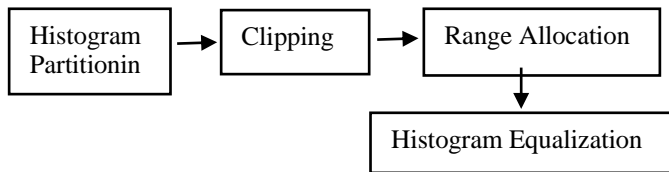### C. Quadratic Dynamic Histogram Equalization (QDHE)

Fig 3: Stages in QDHE

This method produces the better brightness with natural look compared with other existing methods. The equation 3 represents the QDHE formula

$$z(k) = round\ \frac{CDF(k) - CDFmin\ X\ (L-1)}{XY - CDFmin} \qquad (3)$$

The QDHE is described in figure 3, follows in following steps,

3.1 Histogram Partitioning, divides the image into two parts, then it applies median on the sub- parts and histogram is applied on it.

3.2 Clipping, this method overcomes the problem of stretching and prevents the over enhancement and unnatural effects. Clipping process uses thresholding with average of image intensity.

3.3 Range Allocation, the total number of pixels in sub parts are calculated and dynamic range level of histogram for i^{th} value is estimated.

3.4 Histogram Equalization, Explained in section 4 and sub section A.

IV. DENOISING TECHNIQUES

In modern era, due to enhancement in medical images, the evaluation of noise has become complex and advanced. While removing of noise from the image, the quality of the image and other details should be preserved. The denoising techniques discussed here are categorized into three parts, i.e. Filtering domain, Transform domain, and Statistical domain. These domains are further classified into linear and non-linear.
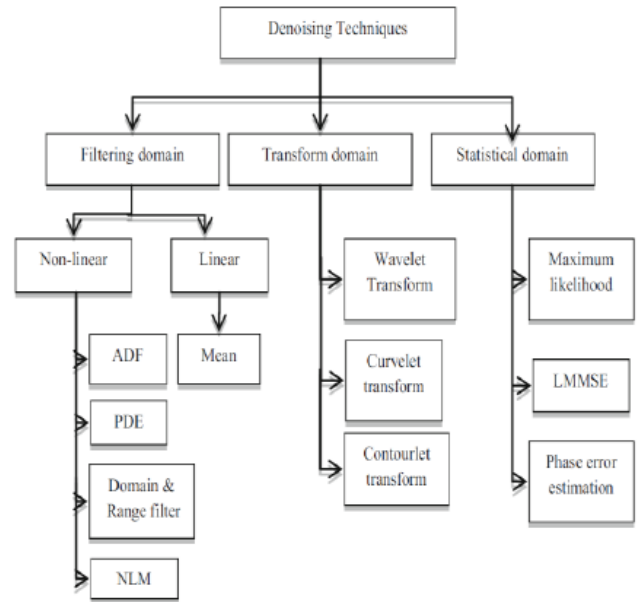

Fig 4: Denoising Techniques

A. Filtering Domain

Filters are classified into two parts i.e. linear filter and non- linear filter. Linear filters are more effective to remove Gaussian noise from the image. These filters produce blurring of edges and to overcome this problem non- linear filters were introduced which helps to smoothen the edges with noise elimination. The combination of domain and range filters introduced a new filter known as bilateral filter. The filter that assigns different weights to neighboring pixels and estimate the mean of them is NLM filter. These NLM filters provide fast computation and increases the performance.

B. Transform Domain

An effective way for spatial variation can be found using wavelet- domain filter. These filters denoise the image and preserves the edges with its underlying details. Adaptive techniques with iterative scheme for denoising to make better precise outcomes. The high- dimensional images can't be solved using wavelet, so curvelet transform and contourlet transform are introduced with hard thresholding for reconstruction the image.

C. Statistical Domain

To estimate and remove the Rician noise combined effect of non- local and maximum likelihood concept. The linear mean square error with local variance and local mean square value are used for removal of Rician noise.

V. COMPARATIVE ANALYSIS OF TECHNIQUES

A comparative analysis is made on diverse techniques for Contrast enhancement and Denoising Techniques. The table 1 and 2 discusses the comparative analysis. The table demonstrates the overview of the different methods or filters helpful to improve the quality of the image with preserving the details of the image.

Table 1: Comparative Analysis of Contrast Enhancement Techniques

Contrast Enhancement Method	Method	Advantage	Disadvantage
HE	Calculation of Distribution Function	Minimum brightness error up to some extent	Better enhancement but introduces some noise
BPHE	Calculate mean of the input image	Minimum brightness error compared to HE	Better than HE with less noises
DISHE	Calculate the median of the image	Almost same brightness error as BPHE	Same as BPHE
DHE	Decomposition of image until dominating portion of the image is eliminated	Poor absolute brightness error	Poor enhancement
BPDHE	To preserve the mean intensity of the image	Improved absolute brightness error	Improved but inclusion of noise
RMSHE	Decomposition of the image using recursive mean of the input image	Improvements in dark images	Over enhanced with noise
RSIHE	Recursive decomposition of image using median value	Better brightness error than RMSHE	Good

Table 2: Comparative Analysis of Denoising Techniques

Denoising Method	Method	Limitation
Linear Filter	Weighted average of intensity values of pixels	Simple to implement but introduces the blurring effect
Wavelet Filter	Recursive decomposition	Degrades the fine details in high noisy image
NLM Filter	Weighted average with standard deviation	Eliminate the non-repeated details but expensive for computation
MRF Filter	Calculating the pdf and cdf	Expensive for computation
Statistical Filter	Conditional distribution of intensity	Fine details are excluded and doesn't preserve edges
Non- linear Filter	Calculate the original value with median value	Reduces the resolution of the image
Anisotropic diffusion	Partial differential equation	Reduces noise with Blur image
Block matching and 3D filter	Fragmentating and Aggregating the weighted average	Blur the edges and noises are not distinguishable

VI. CONCLUSION

This article accentuates the methods related to contrast enhancement and denoising. Few methods perform best results but lack from computation time. There are few parameters like SSIM, PSNR, RMSE, etc., which helps to determine the quality of the image and underlying characteristics or features helpful for analysis of the problem. Each and every filter has their own pros and cons, based on these criteria, the filter has to be selected to preserve the details of the image as discussed in this article. In future, few more methods will be described for comparison with experimental analysis.

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