EFFICIENT QUALITY ANALYSIS OF MRI IMAGE USING PREPROCESSING TECHNIQUES

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Abstract— **Image pre-processing techniques are used to improve the quality of an image before processing into an application. This uses a small neighborhood of a pixel in an input image to get a new brightness value in the output image. These pre-processing techniques are also called as filtration and resolution enhancement. The medical image quality parameters are mainly noise and resolution. The main objective of this paper is to improve the image quality by denoising and resolution enhancement. Most of the imaging techniques are degraded by noise. In order to preserve the edges and contour information of the medical images, the efficient denoising and an improved enhancement technique is required. This paper concentrates the average, median and wiener filtering for image denoising and an interpolation based Discrete Wavelet Transform (DWT) technique for resolution enhancement. The performance of these techniques is evaluated using Peak Signal to Noise Ratio (PSNR). From the results, it reveals that the efficient denoising and resolution enhancement technique is essential for image pre-processing.**

Keywords **- Image preprocessing, Noise, Denoising, Discrete Wavelet Transform, Peak Signal to Noise Ratio.**

I. INTRODUCTION

The Magnetic Resonance Imaging (MRI) is to view the internal structures of the body in detail especially for imaging soft tissues and it does not use any radiations. Brain tumor is an abnormal growth of tissues in the brain and is mainly caused by radiation to the head, genetic risk, HIV infection, cigarette smoking and also due to environmental toxins. Major problem in image segmentation is inaccurate diagnosis of the tumor region which gets reduced mainly due to the contrast, blur, noise, artifacts, and distortion.

No accurate detection of tumor region due to the presence of noise in MR image. Even small amount of noise can change the classification. Gray matter is made up of neuronal cell bodies. The Gray matter includes regions of the brain involved in muscle control, sensory perception such as seeing and hearing, memory, emotions, and speech. White matter is one of the two components of the central nervous system and consists mostly of glial cells and myelinated axons that transmit signals from one region of the cerebrum to another and between the cerebrum and lower brain centers. Noisy image can cause misclassifications of Gray Matter (GM) as White Matter (WM). So the noise is preprocessed using denoising technique. Resolution of an image is always an issue in medical image processing which means loss of quality at the image edges. Resolution enhancement is used to preserve the edges and contour information. The major application of these techniques is detection of tumor cells in human body [1, 2].

Improving the denoising along with the edges is not performed so well in this method [3]. In order to significantly accelerate the algorithm, the filters are introduced to eliminate unrelated neighborhoods from the weighted average used to denoise each image pixel. These filters are based on average gray values as well as gradients, pre-classifying neighborhoods and thereby reducing the quadratic complexity to a linear one and diminishing the influence of less-related areas in the denoising of a given pixel. Part of the ongoing efforts includes the investigation of image characteristics that provide good context classifications for image denoising [4]. Although the inverse filter works well when no noise is present, the Wiener filter performs much better and is more versatile. However, the Wiener filter assumes knowledge of the degradation function and the power spectra of both the noise and the original image. Most image restoration methods require some knowledge of the degradation function, but the Wiener filter in particular presents the additional difficulty of knowing the power spectra, the noise power spectrum can be effectively estimated by analyzing a relatively uniform region of interest in the degraded image. However, obtaining the spectrum of the original signal is more difficult. This requirement makes the Wiener filter less useful in many practical applications. Moreover, the Wiener filter provides a sound theoretical foundation upon which other restoration techniques [5]. Low and high frequency information is effectively extracted by using Haar wavelet transform but noises in the low frequency sub-band are smoothened and in the high frequency sub-bands are sharpened by using the smooth PWL (Piece Wise Linear) filter and another PWL filter respectively has a very satisfactory noise removing property as well as improves the visual quality of images that contain low contrast. The performance of both wavelet transform and PWL has been compared [6]. The image resolution enhancement method using Discrete Wavelet Transform (DWT) is giving better results than any other technique [7].

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II. DENOISING MECHANISM

Most of the imaging techniques are degraded by noise so that the image is preprocessed using denoising technique to extract the useful information. To analyze the medical image i.e segmenting the brain tissues, initially the noise must be removed from the MRI image for retaining the original information. Noise in medical imaging is mainly caused by variation in the detector sensitivity, reduced object visibility (low contrast), chemical or photographic limitations, and random fluctuations in radiation signal.

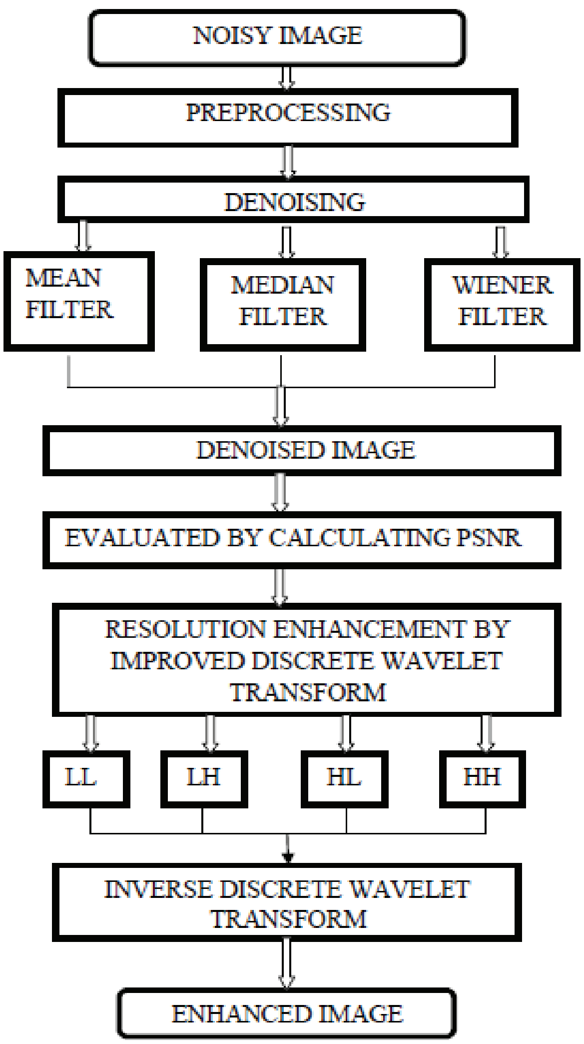

Fig. 1 Overview of the proposed work

Initially the MRI image is taken as an input data. The MRI image is added with Gaussian noise. The denoising is performed using averaging filter, median filter and wiener filter. The performance of these denoising techniques is measured using Peak Signal to Noise Ratio. Fig .1 shows the overview of the proposed work.

A. Gaussian noise

Image noise is defined as the label assigned initially at any pixel and the pixel arrangement will be in a random manner. Gaussian noise is statistical noise that has its probability density function equal to that of normal distribution, also called Gaussian distribution. The mean (average) and variance (standard deviation) are the defining factors. Gaussian noise whose frequency spectrum after a Fourier transform has a bell shaped curve and is symmetric around mean. In order to test the resistance of an image and also to evaluate the performance of the MRI brain image Gaussian noise is added and filtered using some noise filters. Each pixel in the noisy image contains both true pixel value and random Gaussian distribution noise value. Gaussian distribution equation is given below.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} . e^{\frac{-1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (1)$$

where μ denotes mean (average) value of x and σ denotes standard deviation of x.

B. Averaging Filter

Mean filter or averaging filter is a simple linear filter and easy implementation method of smoothing images. Average filter is often used to reduce noise and also reduce the amount of intensity variation from one pixel to another. Here, first take an average that is sum of the elements and divide the sum by the number of elements. Next, replace each pixel in an image by the average of pixels in a square window surrounding this pixel [8, 9, 10]. Fig 2 depicts the functionality behind the averaging filter.

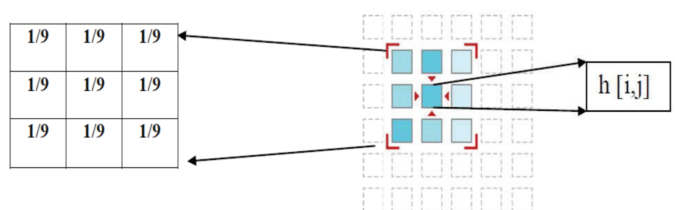

Fig. 2 Functionality behind the averaging filter

$$\mathrm{h}[\mathrm{i},\mathrm{j}] = \frac{1}{\mathrm{M}} \sum_{(\mathrm{k},\mathrm{l}) \in \mathrm{N}} \mathrm{f}(\mathrm{k}.\mathrm{l}) \quad (2)$$

where M is the total number of pixels in the neighborhood N and k, l =1, 2 .. For example, a 3X3 neighborhood about [i, j] yields:

$$\mathrm{h}[\mathrm{i},\mathrm{j}] = \frac{1}{9} \sum_{\mathrm{k}=\mathrm{i}-1}^{\mathrm{i}+1} \sum_{\mathrm{j}=\mathrm{i}-1}^{\mathrm{i}+1} \mathrm{f}(\mathrm{k}.\mathrm{l}) \quad (3)$$

Problem with averaging of filter is that it can remove noise more effectively in larger windows, but also blur the details in an image.

C. Median Filter

Median filtering is a nonlinear operation often used in image processing to reduce noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. The median filter also like mean filter that considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is the

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representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value [11, 12]. Note that if the window has an odd number of entries, then the median is simple to define. It is the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median. In median filtering, the neighboring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel. Fig 3 shows the working principle of median filter.

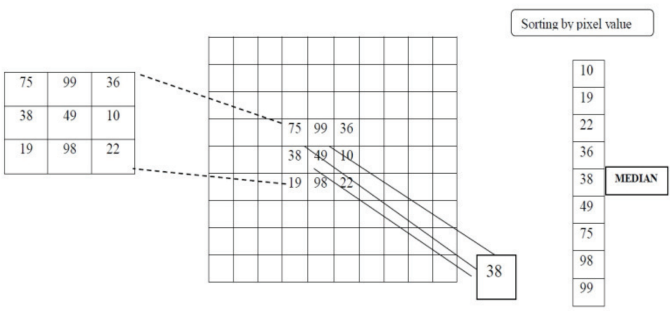

Fig .3 Working principle of median filter

Advantages of median filter are there is no reduction in contrast across steps, since output values available consist only of those present in the neighborhood (no averages). The median is less sensitive than the mean to extreme values (outliers), those extreme values are more effectively removed. The disadvantage of median filter is sometimes this is not subjectively good at dealing with large amount of Gaussian noise as the mean filter.

D. Wiener Filter

The important use of wiener filter is to reduce the amount of noise present in an image by comparison with an estimation of the desired noiseless signal. It is based on a statistical approach. Wiener filters are characterized by three important factors. 1) Assumption: The stationary linear stochastic processes of image and noise with known spectral characteristics or known autocorrelation and cross-correlation 2) Requirement: the filter must be physically realizable/ causal 3) Performance criterion: minimum mean-square error (MMSE).

This filter is frequently used in the process of deconvolution. The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known low pass filter, it is possible to recover the image inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The approach of reducing degradation at a time induces to develop a restoration algorithm. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing [13, 14, 15]. It removes the additive noise and inverts the blurring simultaneously.

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f1, f2) = \frac{H^*(f_1,f_2)S_{xx}(f_1,f_2)}{|H(f_1,f_2)|^2 S_{xx}(f_1,f_2)+S_{\eta\eta}(f_1,f_2)} \tag{4}$$

where $S_{xx}(f_1, f_2), S_{\eta\eta}(f_1, f_2)$ are power spectra of the original image and the additive noise, and H (f_1, f_2) is the blurring filter. It is easy to see that the Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. It is not only performs the deconvolution by inverse filtering (high pass filtering) but also removes the noise with a compression operation (low pass filtering).

III. RESOLUTION ENHANCEMENT

Resolution of an image is always an issue in medical image processing. Resolution is a measure of the amount of detail information in the image. High resolution gives more image details. Initially the image is preprocessed using denoising. After denoising it results in noise reduction and loss of quality at the image edges. Resolution enhancement is used to preserve the edges and contour information of a filtered image. In order to segment an image accurately preserving the edges and contour information is important.

Resolution is the measurement of quality of a denoised image. In order to enhance the resolution of an image an improved discrete wavelet transform is proposed. The improved DWT preserves the edges and the contour information. The performance of resolution enhancement technique is measured using Peak Signal to Noise Ratio.

A. Discrete Wavelet Transform

Wavelets are playing a significant role in many image processing applications. A wavelet transform (WT) is based on wavelets. It is used to analyze a signal (image) into different frequency components at different resolution scales (i.e. multiresolution). This allows revealing image's spatial and frequency attributes simultaneously. Any wavelet-based image processing approach has the following steps. Compute the 2D-DWT of an image, alter the transform coefficients (i.e. sub-bands), and compute the inverse transform.

Wavelet transforms are used in a wide range of image processing applications such as image and video compression, feature detection and recognition, and image denoising. The 2-D wavelet decomposition of an image is performed by applying the 1-D discrete wavelet transform (DWT) along the rows of the image first, and then the results are decomposed along the columns [16 ,17, 18]. One level DWT (with Daubechies 9/7 as wavelet function) is used to decompose an

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input image into different sub-band images. Three high frequency sub-bands (LH, HL, and HH) contain the high frequency components of the input image. The sub-band images are referred to low-low (LL), low-high (LH), high-low (HL) and high-high (HH). The frequency components of those four sub-bands are interpolated to cover the full frequency spectrum of the original image. The interpolation technique is used to increase the number of pixels in an image. The high frequency sub-band of the image is interpolated to low frequency sub-bands of the image to give high resolution enhanced image. Fig 4 and Fig 5 shows the one level decomposition of DWT and block diagram of DWT.

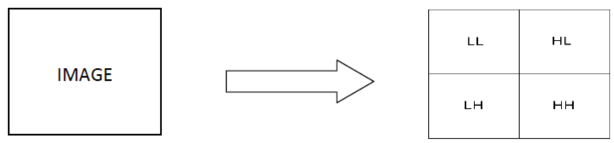

Fig .4 One level decomposition

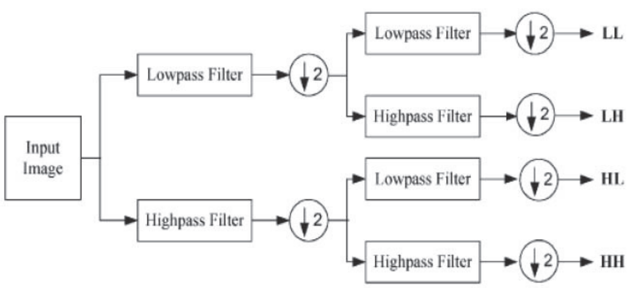

Fig.5 Block Diagram of Discrete Wavelet Transform

The low resolution image (LL sub-band), without quantization (i.e., with double-precision pixel values) is used as the input for the proposed resolution enhancement process. In other words, low frequency sub-band images are the low resolution of the original image. Therefore, instead of using low-frequency sub-band images, which contains less information than the original input image, the input image is used through the decimation process [19, 20]. Hence, the input low-resolution image is decomposed with the half of the decimation factor to improve DWT.

B. Inverse Discrete Wavelet Transform

A process by which components can be assembled back into the original image without loss of information is called reconstruction. Inverse Discrete Wavelet Transform (IDWT) reconstructs an image from the approximation and detail coefficients derived from decomposition. The performance of denoised and enhanced image is evaluated by calculating PSNR value.

IV. QUALITY ANALYSIS

The quality of the preprocessed images is analyzed using Peak Signal to Noise Ratio (PSNR). It is defined as the ratio between the maximum possible power of an image and the power of corrupting noise measure of the peak error. Peak signal-to-noise ratio is measured in decibels between two images. This ratio is often used as a quality measurement between the original and a denoised image. To compute the PSNR, first, calculate the mean-squared error. Mean Square Error (MSE) is the cumulative squared error between the denoised and the original image.

$$\mathrm{MSE} = \frac{\sum_{M,N}[I_{1(m,n)} - I_{2\,(m,n)}]^{\wedge}2}{M*N} \qquad (5)$$

where $I_1(m,n)$ denotes original image, $I_2(m,n)$ denotes denoised image and M and N are the number of rows and columns in the input images

Then it can be very easy to compute PSNR using the following equation:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{R^2}{\mathrm{MSE}}\right) \qquad (6)$$

where , R is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then R is 1. If it has an 8-bit unsigned integer data type, R is 255, etc. Logically, if the PSNR is higher it gives the better quality of the reconstructed image.

V. EXPERIMENTAL RESULTS

The noisy image is taken as the input image and denoising is performed using average, median and wiener filter. Fig 6 and Fig 7 show the input image and denoised images and Fig 8 shows performance of the denoised image.

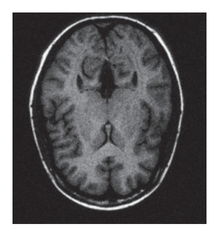

Fig .6 Input image

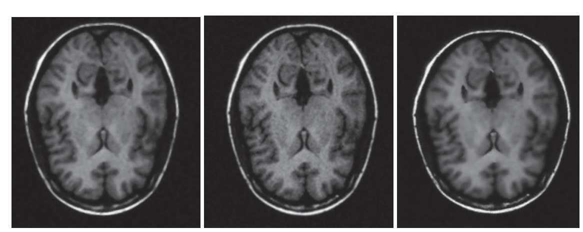

Fig .7 Denoised images a) Averaging filter b) Median filter c) Wiener filter

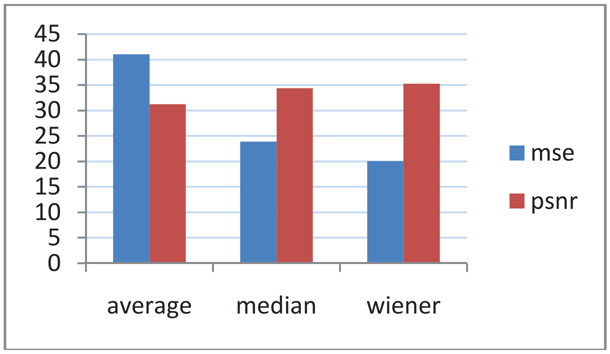

Fig 8 Performance of the denoised image

The denoised image is decomposed into four sub-bands (LL, LH, HL, HH) using interpolation based DWT. Fig 9 shows the decomposition levels of denoised image. Fig 10 depicts the denoised and resolution enhanced image. From the figure, it shows that visually and analytically resolution enhanced image gives better quality for processing an image into different applications. Fig 11 shows the performance comparison of denoised and the resolution enhanced image. The PSNR value of the image is improved from 30dB to 38dB in the resolution enhanced image and error also reduced.

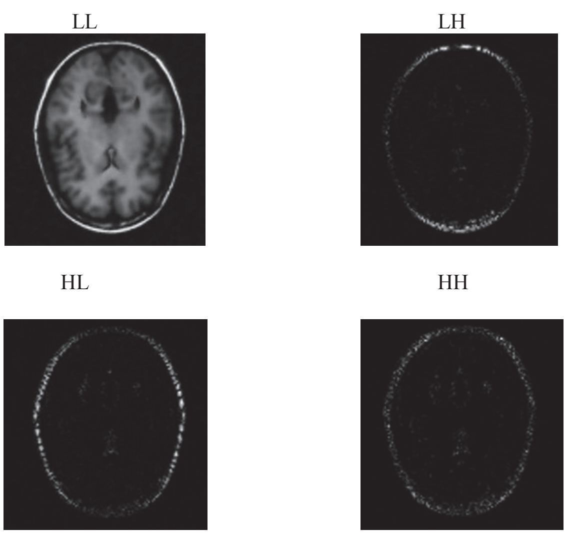

Fig .9 Decomposition levels

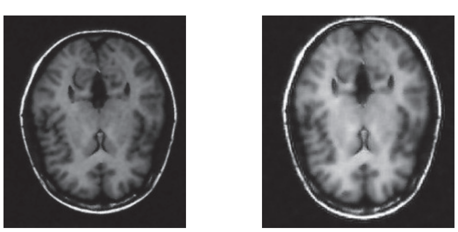

Fig.10 Denoised and the Enhanced image

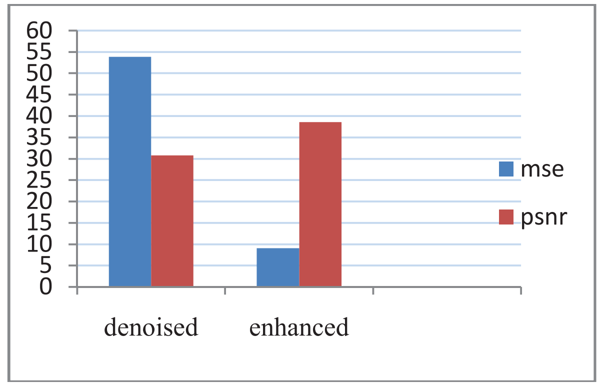

Fig.11 PSNR Value of Denoised and Enhanced image

VI. CONCLUSION

The MR brain image is preprocessed by denoising and resolution enhancement in order to improve the quality of an image. In denoising, the noise gets reduced better by wiener filtering and the resolution of an image is enhanced by interpolation based discrete wavelet transform which preserves the edges and contour information. The quantitative measure shows that the resolution enhancement technique is having better PSNR compared to the denoised image. Thus, while analyzing image preprocessing both the image denoising and resolution enhancement techniques are essential for improving the qualitative performance of an image.

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