Multiresolution Image Decomposition Technique for MR Image Denoising and Enhancement

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Abstract: Magnetic resonance Imaging (MRI) is a medical imaging technique used in radiology to investigate the anatomy and functioning of the body in both health and disease and is widely used in hospitals for diagnosis. MRI is powerful technique for denoising and evaluating to detect the physiological structural abnormalities. Rician noise degrades the MR images and affects the analytic accuracy of the images. Kind of processing these medical images improve their appearance to the viewers in terms of better interaction in features of interest and enhance the visibility in relevant computer aided analysis and diagnosis. A multiresolution technique decomposes the images into multiple scales and is widely used for analyzing the images. In this paper different multiresolution techniques are applied and aimed to improve the quality of given MR images. The image quality has been measured using different parameters. This paper will discuss the multiresolution techniques such as scalar wavelet; multiwavelet and Laplacian pyramid and compare their statistical parameters.

Keywords: Image Denoising, Image Enhancement, Magnetic Resonance Imaging (MRI), Multiresolution Image Decomposition, Wavelet.

I. INTRODUCTION

Medical imaging is the process of collecting information about a specific physiological structure such as tissue or an organ. It uses the predefined characteristic property which is displayed in the image form. The powerful technique used in medical imaging is the Magnetic resonance imaging. Physicians use this technique to detect the structural abnormalities. The image visualization deficiency is caused because there are small differences in the soft tissues. Few years ago, physicians had the medical images or pictures on a light board and they use to make diagnosis using their knowledge. During last twenty years, the progress in the medical MRI technology has created a very large collection of medical imaging techniques which are available to physicians and researchers.

Medical imaging involves a good understanding of imaging medium and object, physics of imaging, instrumentation and often computerized reconstruction and visual display methods. A universal property of images is the presence of a granular pattern of noise which is referred to as Rician Noise, i.e. the MR images are corrupted by noise. The noise in the MR magnitude images obeys rician distribution [1] [2] [3] [5]. This noise is used to refer to the error between the underlying image intensities and the observed data in the given image. Recovery of an original image from a noisy atmosphere is challenging situation. A multiresolution approach [4] provides a powerful tool for image analysis and it is important for enhancing and denoising the quality of MR image. Image denoising has been essential in medical image processing technique.

The experimental results will show the efficacy of proposed method and discuss the multiresolution techniques and compare their statistical parameters.

In this paper, The Peak-Signal-to-Noise-Ratio (PSNR) [1][4], Mean Square Error (MSE) [1][4], Entropy [7] and Time are used to evaluate the enhancement performance of various multiresolution techniques [4]. The PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation, because many signals have a very wide dynamic range. PSNR is usually expressed in terms of the logarithmic decibel scale. It is most easily defined via the mean squared error (MSE) [1] [4] and it is given by (1) as

\[ \text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - k(i,j)]^2 \] (1)
Where, \( I \) and \( k \) are the images.

The PSNR [4] is defined by (2) as

\[
\text{PSNR} = 10 \log_{10} \left( \frac{A^2}{\text{MSE}} \right) = 20 \log_{10} \left( \frac{A}{\text{MSE}^{1/2}} \right)
\]

Here \( A \) is the maximum possible pixel value of the image may be 255. When the two images are identical, the MSE will be zero.

Entropy is defined by (3) [7] as

\[
\text{Entropy} = \sum_i \sum_j p(i,j) \log(p(i,j))
\]

Where, \( p \) is an image. Time is one more parameter which is measured in seconds (sec) and is the time required to denoise and enhance the MR image.

II. RICIAN DISTRIBUTION

Magnetic Resonance Imaging (MRI) is a complex valued data, which is degraded by Rician noise [3] [5]. MR images are ideal for denoising and evaluating many conditions but the diagnostic accuracy of an image will be harmed by the presence of rician noise. The rician noise which degrades the MR image arises from the complex Gaussian noise in the original frequency domain measurements [4]. If the real and imaginary data with mean values \( A_R \) and \( A_I \) respectively, are bankrupt by nonzero mean uncorrelated Gaussian noise with standard deviation \( \sigma \), the PDF of the magnitude data will be a Rician distribution. It is given by (4) [1] [3] [5] as

\[
p(M|A) = \frac{M}{\sigma^2} e^{-\frac{(M^2+A^2)}{2\sigma^2}} I_0\left(\frac{2AM}{\sigma^2}\right)
\]

Where, \( I_0 \) is the zeroth order Bessel function of the first kind [1] and \( M \) denotes the pixel variable of the magnitude of an image [1] and \( A \) is given by (5) [1] as

\[
A = (A_R^2 + A_I^2)^{1/2}
\]

The rician distribution tends to Rayleigh distribution when the SNR goes to zero and at high SNR it tends to Gaussian distribution. The moments of the rician density function can be expressed systematically as a function of the confluent hyper geometric function [1] and is given by (6) [1] as

\[
E[M^V] = 2(\sigma^2)^{V/2} \Gamma(1+V/2) \Gamma(1+V/2; -A^2/2\sigma^2)
\]

For even moments, it becomes a simple polynomial in its argument. Particularly, the second moment is given by (7) [1] as

\[
E[M^2] = 2\sigma^2 + A^2
\]

III. MULTIRESOLUTION IMAGE DECOMPOSITION TECHNIQUES

Multiresolution techniques are mathematical functions that decompose the images into several scales. In this paper we are considering three mathematical functions. They are Scalar wavelets, Multiwavelets and Laplacian Pyramid. These functions decompose the images into a hierarchy of scales ranging from the coarsest scale to the finest one.

A. Discrete Wavelet Transform

The Discrete wavelet Transform (DWT) provides sufficient amount of information and offers significant reduction in computation time. Wavelet coefficients of signal are the projections of the signal onto the multiresolution subspaces. Wavelets are the functions generated from one single function (basis function) called the prototype or mother wavelet by dilations (scalings) and translations (shifts) in time (frequency) domain. If the mother wavelet is denoted by \( \Psi(t) \) and other wavelets \( \Psi_{a,b}(t) \) can be represented by (8) as
\[ \Psi_{a,b}(t) = \frac{1}{|a|} \Psi\left(\frac{t-b}{a}\right) \]  
(8)

Where, \( a \) and \( b \) are two arbitrary real numbers. The variables \( a \) and \( b \) represent the parameters for dilations and translations, respectively.

The properties are Symmetry, compact support, Number of vanishing moments and smoothness and regularity [1]. The two dimensional DWT represents a real valued image in terms of shifts and dilations of a low pass scaling function and band pass wavelet. The discrete 2-D wavelet functions \( \Psi_{j,k} \) and scaling functions \( \Phi_{j,1} \) have several indices, here \( j \) is corresponding to the scale, \( o \) is corresponding to the wavelet orientation (horizontal, vertical or diagonal) \( k,1 \) is corresponding to the position. In order to keep notation to the minimum, an abstract index \( I \) is employed for these indices. Furthermore, 2-D wavelet functions, scaling functions, and images are vectorized by stacking the columns of each, and a single abstract spatial index \( m \) is used. The \( I^{th} \) scaling coefficient of the image \( S \) is computed by (9) as

\[ C_{I} = \sum_{m} \Phi_{I}[m]s[m] \]  
(9)

Similarly the \( I^{th} \) wavelet coefficient is computed by (10) as

\[ d_{I} = \sum_{m} \Psi_{I}[m]s[m] \]  
(10)

The scaling and wavelet coefficients are collectively denoted by vectors \( c \) and \( d \) respectively. The reason that the DWT is so enviable is that the wavelet transforms of natural signals and images tend to be very sparse, with a few large scaling and wavelet coefficients dominating the representation. That is, wavelet transform tend to compress real – world signals. The compression property of the wavelet transform is attributed to the fact that the wavelet coefficients of polynomial signals are exactly zero. This fact is a consequence of the “vanishing” moments [1] of the wavelet functions. In Discrete wavelet transform domain, one low pass coefficient is followed by one high pass coefficient. Two-level decomposition of image sub bands is shown in fig: 1.a. One-level decomposition of human brain image for discrete wavelet is shown in fig: 1.b.

**B. Multiwavelet Transform**

Multi wavelet transformation is a new concept of wavelet transformation architecture, which has more than one scaling function \( \Phi(t) \) and wavelet function \( \Psi(t) \). Multiwavelet is usually indicated by multi-dimensional vector function. In multiwavelet transform, in this paper, we use multiwavelet as transform basis. Multiwavelets have two or more scaling functions and mother wavelet for signal representation. The properties of GHM multiwavelet filter are orthogonality, symmetry and compact support. To implement the multiwavelet transform [1], we require a new filter bank structure where the low pass and high pass filter banks are matrices rather than scalars. [1]

Multiwavelet transform domain that there are first and second low pass coefficient followed by first and second high pass coefficient shown in fig: 3 [1]. And the two level image sub bands for multiwavelet transform are shown in fig: 4.a. [1].
Since the GHM filter has two scaling and two wavelet functions, it has two low pass sub bands and two high pass sub bands in the transform domain which is shown in fig: 4.b. Human brain image of 256x256 after the GHM multiwavelet transform as an example. The transformed human brain image has in each dimensions two low frequency and two high frequency sub-images. It is easy to see that there are similarities between low frequency sub-images so that it is possible to apply a certain prediction rule to remove the redundancy between these sub bands.

The Laplacian pyramid [4] [6] is ubiquitous for decomposing images into multiple scales and is widely used for image analysis. Over-complete decomposition based on difference-of-low pass filters, the image is recursively decomposed into low pass and high pass bands. Laplacian pyramids have been used to analyze images at multiple scales for a broad range of applications such as compression and harmonization. The name Laplacian Pyramid is a misnomer; it should be called the Difference of Gaussian Pyramid, since each level (e.g., image) is given roughly by smoothing with two Gaussians of different sizes, the subtracting and sub sampling.

Pixels to pixels correlation are first removed by subtracting a low pass filtered copy of the image from the image itself. The difference or error image has low variance and entropy, the low pass filtered image may be represented at appropriately expanded scales generates a pyramid data structure. Let I be the original image and J be the result of applying an appropriate low pass filter to go. The prediction error E is given by E1=I1-J1. The reduced image I1 itself low pass filtered to yield I2 and a second error image is obtained E2=I2-J2. By these steps we obtain two dimensional arrays E1, E2…En. If we now imagine these arrays stacked one above another, the result is a tapering pyramid data structure shown in fig.6. The value at each node at the pyramid represents the difference between two Gaussian like and related functions convolved with the original image.
The difference between these two functions is similar to the Laplacian operators. The value at each node in the Laplacian pyramid is the difference between the convolutions of two equivalent weighting functions with the original image. Again this is similar to convolving an appropriately scaled Laplacian weighting function with the image. The node value can be obtained directly by applying this operator. The pyramid decompositions are performed on each source image; all these decompositions are integrated to form a composite representation. Image pyramid decomposition is shown in fig: 4. [4]

Fig: 4. Image Pyramid Decomposition

IV. EXPERIMENTS AND RESULTS

To test our proposed algorithm we took a Magnetic resonance imaging of Human Brain. The size of a medical image of human brain is 256x256. Fig: 5 (1 and 2 are images of acoustic neuroma MRI, image names: 6.jpg and 9.jpg as used in project work.) [8], shows the samples of the human brain. In this, the input image does not give the suitable information for the diagnosing purpose.

The rician or rice noise is used to refer to the error between the underlying image intensities and the observed data [4]. The rician noise is added to the input image samples which results in the noisy distributed images shown in fig: 7.

This section indicates that the results from the experiment using the proposed multiresolution techniques [4] are presented in fig: 8. Background part is excluded when our proposed noise removal algorithm is applied in MR Image. Fig: 9, shows that the rician noise is removed significantly using scalar wavelet and fig: 11 show that of using multiwavelet. The accuracy of an image after applying noise removal algorithm, we can observe the image for out looking. It shows the denoised and enhanced output images provide more accurate information than the original input image.

To compare the restoration performance of different methods, various quality indices are used. Performance evaluation involves a quantitative criterion (visual assessment) that reflects the ability of the algorithm to suppress noise while preserving image details.

Fig: 5. Original images

Fig: 6. Rician Distributed Images
V. CONCLUSION

In this paper, we present an efficient and a simple technique to remove the noise from the MR images. A multiwavelet system can provide simultaneously perfect reconstruction while preserving length (orthogonality), a high order of approximation (vanishing moments) and good performance at the boundaries (via linear-phase symmetry) [1] [4]. Multiwavelets offer better performance for image processing applications compared with scalar wavelets since scalar wavelet does not possess all the above properties. But the Laplacian Pyramid [4] [6] decomposition method provides finer performance than the other methods.

<table>
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<tr>
<th>TABLE: 1. SCALAR WAVELET</th>
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<th>TABLE: 2. MULTIWAVELET</th>
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<th>TABLE: 3. LAPLACIAN PYRAMID</th>
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Table: 1, 2, 3 give the performance parameters of multiresolution techniques. The experimental results using MATLAB show that the performance parameters for the Laplacian Pyramid technique are better than the scalar wavelet and multiwavelet.
REFERENCES


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