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A Combined Denoising Approach for Effective Diagnoses of Medical Images in a Multiresolution Framework

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***Abstract*— Magnetic Resonance (MR) imaging is a powerful tool to investigate the internal structure and functional characteristics in the human body. However MR images are affected by different kinds of noise during the acquisition process. In this paper we consider MR images corrupted with white Gaussian noise. Many different algorithms have been developed to denoise Gaussian noise perturbed MR images. These methods fail to preserve the edges and fine structures which are very crucial in case of medical images. In this paper, we propose to carry out denoising in the wavelet domain combining the special features of nonlocal means filter. We have demonstrated our results with the quality matrix PSNR.**

***Index Terms*— Magnetic Resonance Imaging, Gaussian noise, Nonlocal-means**

I. Introduction

Magnetic Resonance Imaging (MRI) has emerged as a powerful technology over the last few decades. This technology has blessed the mankind as studying the structural features and functional characteristics of the internal organ has become relatively easy and simple. MR images are affected by several artefacts and noises during acquisition process. Frequency coils as well as preamplifiers which are part of the acquisition system tend to introduce some sort of thermal noise in MR imaging. The noise interference is definitely degrades the acquisition of any quantitative measurements from the data.

Noise removal can be dealt with in two different ways. The random noise can be dealt in a better way by averaging multiple images of the same data. But this procedure is quite slow and some time introduces motion artifacts and hence not suitable in clinical MR imaging where having higher speed is the constraint. In the second method, after image acquisition some suitable image denoising techniques are applied which provide reliable and fast results. Many post-denoising methods have been proposed in literature. A few of them include Bayesian approaches [1], anisotropic diffusion filter [2], total variation minimization [3], adaptive smoothing [4] and wavelet thresholding [5, 6].

In medical images edges and small structures play very important role as these provide additional information to the physician for better diagnoses. Hence denoising medical image is a challenging task. In this paper we preserve the edges and small structural details of MR images by multiresolution denoising technique. This technique has been used to decompose the image into detail and approximate subbands with various scales. Further various thresholding techniques can be used for effective denoising. The widely used techniques include Hard and soft thresholding, VisuShrink [5], Sureshrink [7] [8], Bayes shrink thresholding [5], [9] techniques which have been explained in the following section. In the proposed method these techniques have been used in conjunction with nonlocal means (NLM) denoising [10]. NLM filter has been employed to the approximate coefficients for edge preserved denoising. The details of NLM filtering has been provided in the respective section. In this paper we use PSNR (peak signal to noise ratio) as quantitative measure and visual comparison for qualitative measure.

The paper is organized in the following manner. In section II, we provide the brief introduction of multiresolution techinque followed by the brief introduction of nonlocal means denoising. The proposed method is also explained in the same section. In section III we provide the results with discussion and section IV concludes the paper.

II. The proposed method

In this work we propose to carry out multiresolution technique (wavelet transform) to denoise detail coefficients by applying appropriate thresholding technique. Further, noise present in the approximate coeffients will be reduced by applying nonlocal means (NLM) filter. In this section we introduce in brief both wavelet transform and nonlocal means filter.

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Wavelet transform:
Wavelet transform is a time frequency analysis method where the information regarding time as well as frequency can be obtained [11]. This techniques works on the principle that noise mostly belongs to high frequency information. The given image will be divided into different blocks based on its various frequency contents. Hence it becomes easy to remove high frequency noise by setting subblock to zero. The procedure to denoise is as follows: wavelet transform; threshold of wavelet detail coefficients and reconstruction. Wavelet transform can be divided in two broad categories: continuous, and discrete. We process on discrete as computer programs use discrete wavelet transform and it is very efficient from the computational point of view. Wavelets provide a framework for signal decomposition in the form of a sequence of signals known as approximation signals with decreasing resolution. The methods based on wavelet representations yield very simple algorithms that are more powerful and easy to work.

Down-sampling and up-sampling filter banks are the major parts of denoising process. The Fig 1 shows the two stage down sampling filter bank. A reconstruction of the original fine scale coefficient of the signal made from a combination of the scaling function and wavelet coefficient at a coarse resolution. Fig 2 shows the structure of two stages up sampling filter banks in terms of coefficients i.e., synthesis from coarse scale to fine scale.

Computing the appropriate values for thresholding plays a vital role in denoising. When the image is transformed by wavelet transform (WT), the energy will be concentrated on the small number of wavelet coefficients, whereas noise will be distributed on the entire time axis. While processing, the coefficients of interest will be retained and others set as zero. Thus the noise will be suppressed. Different threshold values can be set depending on the type of the image and noise level. However the following method has to be followed while applying the appropriate threshold values.

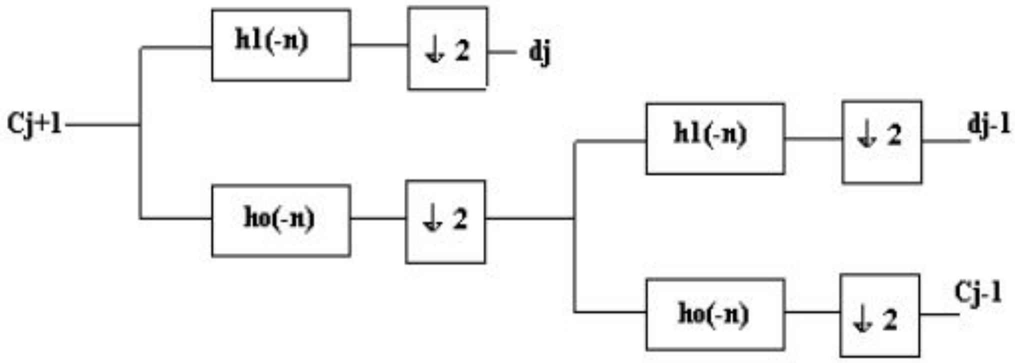

Figure 1: Two stage down sampling filter bank.

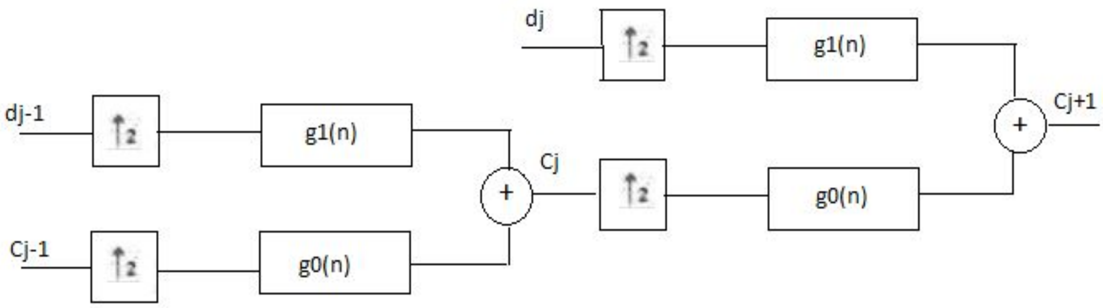

Figure 2: Two stage up-sampling filter bank.

Consider a signal of interest to be x(t) and noise to be n(t). Add these components to get noisy data y(t) i.e.,

$$y(t) = x(t) + n(t)$$

First image has to be decomposed by selecting appropriate wavelet function. Next level of decomposition has to be selected. More the decomposition levels, more will be the noise removal. In this stage appropriate value of the threshold has to be selected. Image reconstruction is the final step.

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Coefficients with threshold processed will be used to reconstruct the image by inverse wavelet transform. Removing noise becomes easy in the transformed domain. Here filter coefficients are removed those are associated with noise. It is observed that some noise still appears at the approximate coefficients i.e., at the low frequency components. Hence we propose to use nonlocal means filter to smooth these coefficients.

In hard thresholding, the wavelet coefficients below a given value are set to zero, while in soft thresholding the wavelet coefficient are reduced be a quantity to the threshold value.

Hard threshold: y=x if |x|>λ
y=0 if |x|<λ

Soft threshold y=sign(x) (|x|- λ)

where x is input signal, y is the signal after threshold and λ is the threshold value.

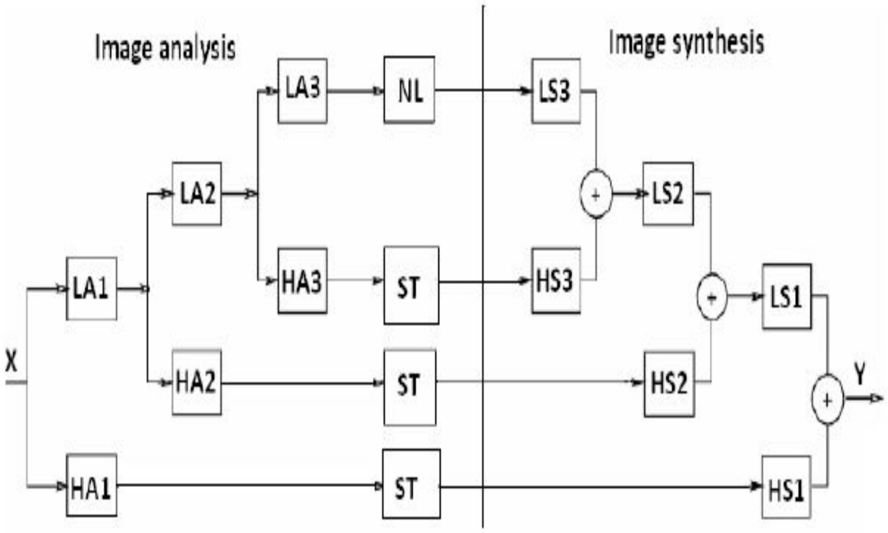

Figure 3. Illustration of the proposed method of denoising. Here NL and ST denote nonlocal means and soft thresholding respectively.

Nonlocal means filter:

The observation model for a noisy image u is written as

$u = v + \eta$

where v is the original image and n is a zero mean additive random noise with standard deviation σ. In NLM strategy each noisy pixel is replaced by an weighted average of all the pixels in the image.

$$v(i) = \sum_j w(i,j)u(j)$$

where weight $w(i,j)$ is computed by pixel-wise intensity distance between two patches and is given by

$$w(i,j) = \frac{1}{Z(i)} \exp\left(\frac{-\|u(N^P(i)) - u(N^P(j))\|_2^2}{h^2}\right)$$

Here $N^P(i)$ and $N^P(j)$ represent the square patches of size (2p+1) X (2p+1) centered at pixels i and j, respectively and p is half length of the patch. Z is the normalization parameter.

Methodology:

Here MR images corrupted with i.i.d random noise have been considered which are further decomposed using DWT transform to obtain MR coefficients. The different thresholding techniques used to denoise MR detail coefficients are as below:

Universal threshold is the optimal threshold in the asymptotic sense and minimizes the cost function of the difference between the function. Universal threshold may give better estimate for the soft threshold if the number of sample is large [5] [9]. The universal threshold is defined as,

$$T=\sigma\sqrt{2\log(N)}$$

σ and N being the noise variance and signal length respectively.

VisuSrink [5] uses threshold value proportional to the standard deviation of the noise and also follows hard threshold rule. Noise estimation can be given by median absolute deviation given by

$$\sigma = \frac{Median(|g_{j-1}|: k = 0,1, \dots 2^{j-1} - 1)}{0.6745}$$

Sure Shrink thresholding proposed by Donoho et al. is the combination of universal threshold and SURE threshold. In Sure Shrink thresholding, a threshold value is chosen by Stein’s unbiased risk estimator. It is a combination of the universal threshold and the SURE threshold. In Sure Shrink thresholding mean squared error is minimized.

$$MSE = \frac{1}{n^2} \sum_{x,y-1}^{n} (Z(x,y) - S(x,y))^2$$

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where $Z(x,y)$ is the estimate of the signal, s(x,y) is the original signal.

The main aim of the Bayes Shrink estimator is to minimize the Bayesian risk, and hence its name, Bayes Shrink[12]. The Bayes threshold, t_B, is defined as

$$t_B = \frac{\sigma^2}{\sigma_s}$$

where σ^2 is the noise variance and σ_s is the signal without noise.

The proposed change in this technique is to apply a nonlocal means filter to the approximate coefficients as illustrated in Fig 3.

III Experimental Results

We experimented on numerous data sets of T1- weighted (T1-w) and T2-weighted (T2-w) MR images. However, for the illustrative purpose in Fig 4 we provide two MR images of T1-w and T2-w of spatial resolution 256X 256 in each case. Images have been simulated with i.i.d random noise having noise variation in the range σ=10~30.

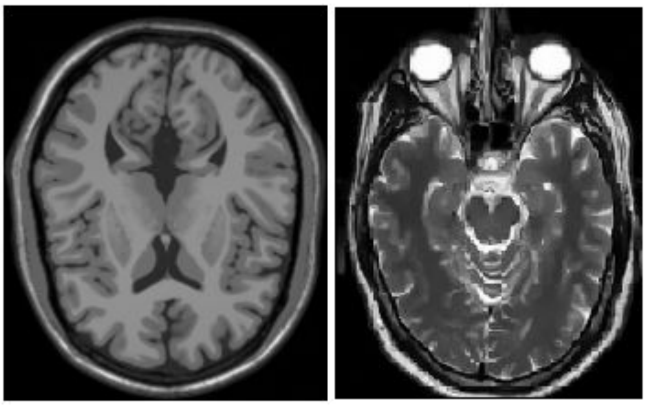

Figure4. Samples of the MR images used in experimentation. (left to right): T1-weighted MR image and T2-weighted MR image.

Quality matrix used for the evaluation is PSNR and visual comparison. PSNR results for the proposed method are tabulated in Table.1. From the table we observe that the proposed method with Visushrink thresholding provides results better than Universal, Hard and Soft thresholding. However superior results are obtained with Sureshrink thresholding. In Hard and Universal thresholding, threshold value will not be adjusted in accordance with the variations in the noise level. Noise will be removed uniformaly in all regions and hence least PSNR values are observed for these methods.

Visual comparisons have been shown in Fig 5. The edges and small details in the resultant image is highlighted with green colored square boxes. Here we observe that universal method is not able to remove the noise quite satisfactorily compared to all other thresholding techniques, whereas SureShrink method is able to retain the edges and small structural details in addition to removing the noise quite substantially.

Methods	Denoised Image (PSNR in dB)					
	σ=10		σ=20		σ=30	
	T1-w	T2-w	T1-w	T2-w	T1-w	T2-w
Hard	34.15	34.23	32.23	32.38	29.98	30.13
Soft	34.66	34.73	32.78	32.91	30.23	30.51
VisuShrink	35.12	35.29	32.98	33.13	30.68	30.78
Universal	33.98	34.12	31.79	31.89	30.11	30.33
Sureshrink	**36.87**	**37.11**	**34.45**	**34.61**	**32.63**	**32.79**
Bayesshrink	36.53	36.71	34.23	34.55	32.53	32.93

Table 1.Illustrationof the denoising results for various thresholding techniques

IV CONCLUSIONS

In this article, we have proposed an edge preserving multiresolution based denoising for MR images in conjunction with the NLM method. In the proposed method various thresholding technique has been applied to smooth the detailed coefficients. The approximate coefficients are further smoothed by NLM filter. The proposed algorithm works very well for MR data set corrupted with a wide range of input noise. It is observed from the quality matrices that the accuracy of the algorithm is maximum with SureShrink thresholding.

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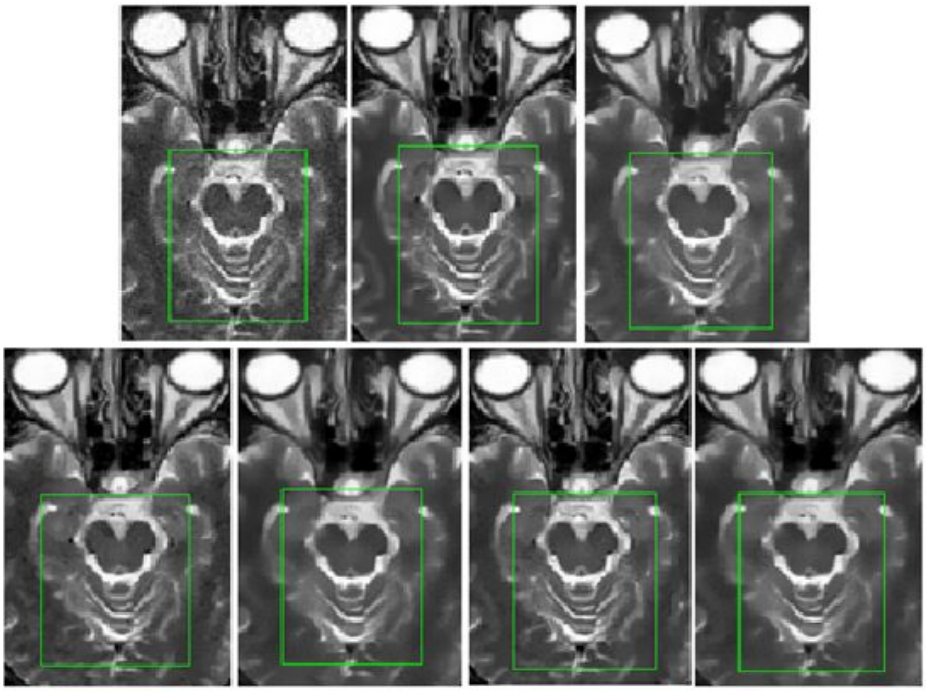

Figure 5. Comparisons of the denoising results of the proposed method on T2-w MR image with various denoising techniques (left to right, top to bottom); Noisy image, results of SureShrink, Visushrink, Universal, Soft, Hard and Bayes thresholding

VI REFERENCES

[1] S. Geman, D. Geman. Stochastic relaxation, Gibbs distribution, and the bayesian restoration of images. IEEE Trans Pattern Anal Mach Intell 1984; 6:721-741.
[2] Malik J, Perona P. Scale-space and edge detection using anisotropic diffusion. IEEE Trans Pattern Anal Mach Intell. 1990; 12:629-39.
[3] Fatemi E, Rudin LI, Osher S. Nonlinear total variation based noise removal algorithms. Physica D 1992; 60:259-68.
[4] P. Saint-Marc, J.-S. Chen, G. Medioni. Adaptive smoothing: A general tool for early vision. IEEE Trans Pattern Anal Mach Intell 1991; 13(6):514-529.
[5] Donoho DL.De-noising by soft-thresholding. IEEE Trans Inform Theory 1995; 41:613-27.
[6] D. L. Donoho, I. M. Johnstone. Ideal spatialadaptation by wavelet Shrinkage. Biometrika 1994; 81(3):425-55.
[7] F. Luiser, T. Blu, and M.Unser, A new SURE approach to image denoising: Inter-scale orthonormal wavelet thresholding, IEEE Trans. Image Process., vol 16, no3, pp. 593-606, Mar.2007.
[8] X.P.Zhang and M.D.Desai, " Adaptivedenoising based on SURE risk", IEEE Signal Processing Letters, vol 5, no.10, pp. 265-267, Oct 1998.
[9] Mark J.T.Smith and stievenL.Eddins," Analysis/Synthesis techniques for subband image coding, " IEEE Trans. Acoust., Speech and Signal Process., vol 38, no.8, pp.1446-56 Aug 19990.
[10] A.Buades, B.Coll, J.M.Morel. A non-local algorithm for image denoising. IEEE Computer Vision and PattRecog 2005; p. 60–65.
[11] RaghuveerM.Rao., A.S.Bopardikar, Wavelet Transforms; Introduction to theory and application published by Addison Wesley 2001, pp. 1-26.
[12] Chang, S. G., Yu, B., and Vetterli, M, Adaptive wavelet thresholding for image denoising and compression. IEEE Trans. on Image Proc., 9, 1532-154

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