Academic Science

International Journal of Electronics, Electrical and Computational System
IJEECS
ISSN 2348-117X
Volume 6, Issue 7
July 2017

Denoising the Spectral Information of Non–Stationary Image using DWT

Dr.DolaSanjayS[1], P. Geetha Lavanya[2], P.Jagapathi Raju[3], M.Sai Kishore[4], T.N.V.Krishna Priya[5]

[1]Principal, Ramachandra College of Engineering, Eluru, Andhra Pradesh, India.

[2,3,4,5]B.Tech.Students,Department of Electronics & Communication Engineering, Ramachandra College of Engineering, Eluru, Andhra Pradesh, India.

ABSTRACT:

The image de-noising naturally corrupted by noise is a classical problem in the field ofsignal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Gaussian noise using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform. We propose an adaptive method of image de-noising in the wavelet sub band domain. This approach is based on threshold estimation for each sub band of the wavelet decomposition of a noise-contaminated image, by considering that the sub band coefficients have a Generalized Gaussian Distribution (GGD). Hence, it improves the performance of the MATLAB2-D de-noising function, which defines a global threshold for all the sub bands of a Discrete Wavelet Transform (DWT). Also, the effectiveness of the criteria ,which are the same with those of MATLAB, that define the threshold levels is evaluated. The experimental evaluation of our proposed shows that it removes noise significantly and more effectively than the existed MATLAB function by usingDaubechies wavelet when compared to other wavelets.

Keywords: Wavelet, Gaussian, Daubechies, haar, symlets, bi-orthogonal, De-noising,PSNR, MSE.

INTRODUCTION

In digital imaging, the acquisition techniques and systems introduce various types of noises and artifacts. Denoising is more significant than any other tasks in image processing, analysis and applications. Reserving the details of an image and removing the random noise as far as possible is the goal of image de-noising approaches. Besides the noisy image produces undesirable visual quality, it also lowers the visibility of low contrast objects. Hence noise removal is essential in digital imaging applications in order to enhance and recover fine details that are hidden in the data.

Image de-noising is the fundamental problem in Image processing. Wavelet gives the excellent performance in field of image de-noising because of sparsity and multi resolution structure. With the popularity of Wavelet Transform for the last two decades, several algorithms have been developed in wavelet domain. The focus was shifted to Wavelet domain from spatial and Fourier domain.

In this approach multilevel discrete wavelet transform (Dwt) is applied on the Magnetic Resonance Image(MRI) skull image of size 1100 X 731.The approach uses Daubechies 9 filter which provides good quality image reconstruction after inverse wavelet transform (IDWT). Thresholding is applied on detail sub–bands but not on the approximation sub–band. MATLABv2014a has been used for the modelling purpose. The obtained results has high peak signal-to-noise ratio (PSNR) value and effective mean –square-error(MSE) essential for reconstruction of good quality image after de-noising.

PROBLEM DESCRIPTION

MRI system is working on the principles of nuclear magnetic resonance (NMR), to map the spatial location and associated properties of specific nuclei or protons in a subject using the interaction between an electromagnetic field and nuclear spin. It detects and processes the signals generated when hydrogen

atoms are placed in strong magnetic field and excited by a resonant magnetic excitation pulse. The human body is largely composed off at and water molecules. Each water molecule has two hydrogen nuclei or protons. These hydrogen protons are usually Imaged to demonstrate the physiological or pathological alterations of human tissues.

MRI, even if the scanner technology has undergone tremendous improvements in spatial resolution, acquisition speed and signal -to-noise ratio(SNR),the diagnostic and visual quality of MR images are stillaffected by the noise in acquisition. However, MRIs contain varying amount of noise of diverse origins, including noise from stochastic variation, numerous physiological processes, eddy currents, artifacts from the magnetic susceptibilities between neighbouring tissues, rigid body motion, non rigid motion and other sources. Identifying and reducing these noise components in MR images is necessary to improve the validity and accuracy of studies designed to map the structure and function of the human body. The main noise in MRI is due to thermal noise that is from the scanned object. The variance of thermal noise can be described as the sum of noise variances from independent stochastic processes representing the body, the coil and the electronics. Such a noise degrades the acquisition of any quantitative measurements from the data. The signal-to-noise ratio depends on static field intensity, pulse sequence design, tissue characteristics, RF coil and sequence parameters, such as voxel size (limiting spatial resolution), number of averages in the image acquisition and receiver bandwidth.

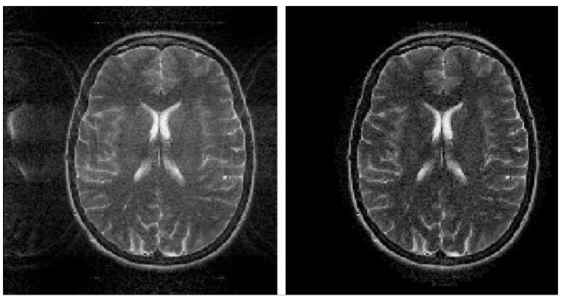
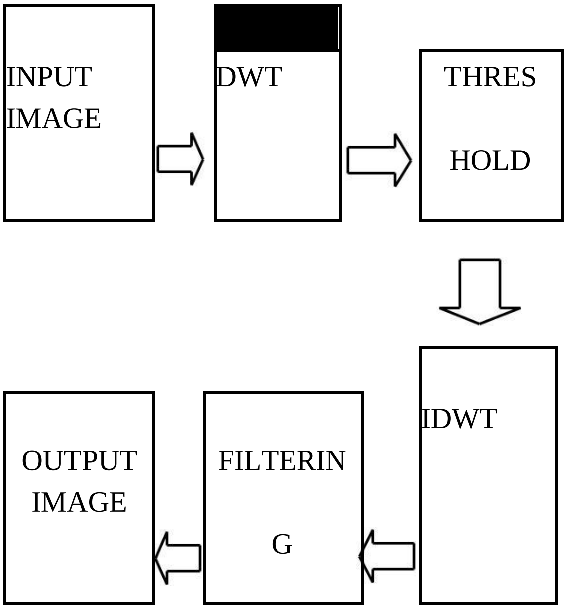


Figure3.1: MR image with noise

PROPOSEDALGORITHM

The image usually has noise which is not easily eliminated in image processing. According to actual image characteristic, noise statistical property and frequency spectrum distribution rule, people have developed many methods of eliminating noises, which approximately are divided into space and transformation fields. The space field is data operation carried on the original image, and processes the image grey value, like neighbourhood average method, wiener filter, centre value filter and so on. The transformation field is management in the transformation field of images, and the coefficients after transformation are processed. Then the aim of eliminating noise is achieved by inverse transformation, like wavelet transform. Successful exploitation of wavelet transform might lessen the noise effect or even overcome it completely. There are two main types of wavelet transform - continuous and discrete. Because of computers discrete nature, computer programs use the discrete wavelet transform. The discrete transform is very efficient from the computational point of view. In this paper, we will mostly deal with the modelling of the wavelet transform coefficients of natural images and its application to the image de-noising problem. The wavelet transform has become an important tool for this problem due to its energy compaction property. Indeed, wavelets provide a framework for signal decomposition in the form of a sequence of signals known as approximation signals with decreasing resolution supplemented by a sequence of additional touché scaled details.



De-noising or estimation of functions, involves reconstituting the signal as well as possible on the basis of the observations of a useful signal

International Journal of Electronics, Electrical and Computational System
IJEECS
ISSN 2348-117X
Volume 6, Issue 7
July 2017

corrupted by noise. The methods based on wavelet representations yield very simple algorithms that are often more powerful and easy to work with than traditional methods of function estimation. It consists of decomposing the observed signal into wavelets and using thresholds to select the coefficients, from which a signal is synthesized. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or de-noising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version.

Daubechies: In griddaubechies, one of the

world of wavelet research, invented what are called compactly supported orthonormal wavelets – thus making discrete wavelet analysis practicable. The names of the daubechies family wavelets are written dbN, where N is the order, and db the surname of the wavelet.Thedb1wavelet, is same as Haar wavelet.

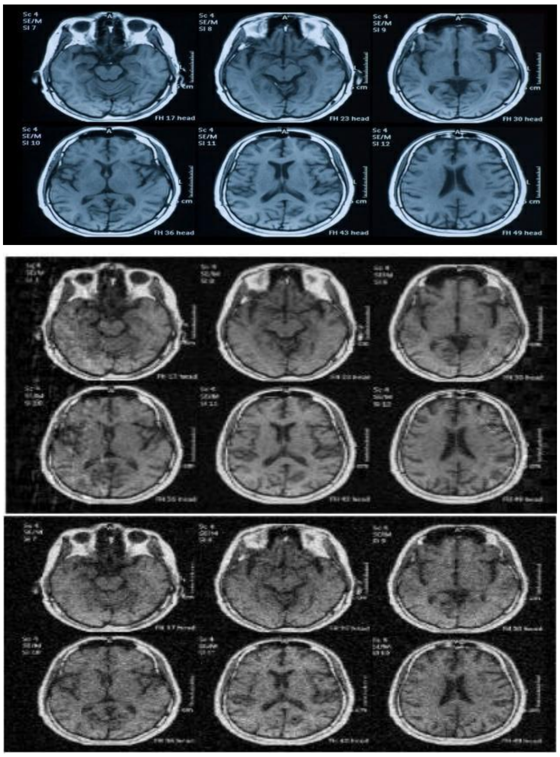
5.5Haarwavelet:

Haar wavelet transform by computing the running averages and differences via scalar products with scaling signals and wavelets the only difference between them consists in how these signals and wavelets are defined. This wavelet type has balanced frequency responses but nonlinear phase responses. Daubechies wavelets use overlapping windows so the high frequency coefficient spectrum reflects al high frequency changes. Therefore daubechies wavelets are useful in compression and noise removal.

5.6SymletWavelet: In sym N, N is the order. Some authors use 2N instead of N. The symlets are nearly bi-orthogonal wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. Symlet wavelets used in practice are also selected even number of wavelets as Daubechies. Symlets when applied to signal performs better and SNR of reconstructed or de-noised signal is improved.

5.7Biorthogonalwavelet:

A bi orthogonal wavelet is a waveletwhere the associated wavelet transform is invertible but not necessarily orthogonal. Design Image with Gaussian noiseing bi orthogonal wavelets allows more degrees of freedom than orthogonal wavelets. In order to gain greater flexibility in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi orthogonal, bi orthogonal or non-orthogonal wavelet bases. Bi orthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. In the bi orthogonal case, rather than having one scaling and wavelet function, there are two scaling functions that may generatedifferent multi resolution analysis, and accordingly two different wavelet functions



Images without any noise,with added Gaussian noise and the de-noised image by using symlets wavelet transform

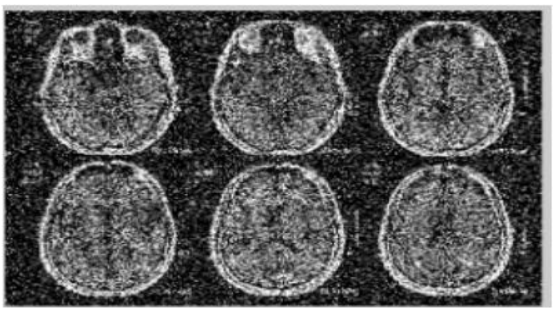
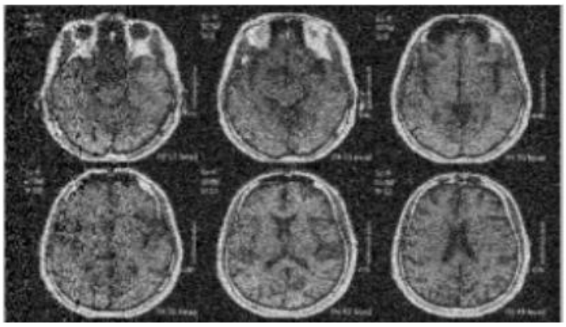


Image with Gaussian noise



De-noised image by using bi or wavelettransform

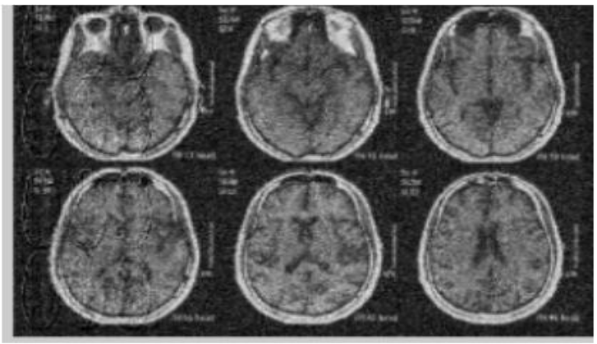
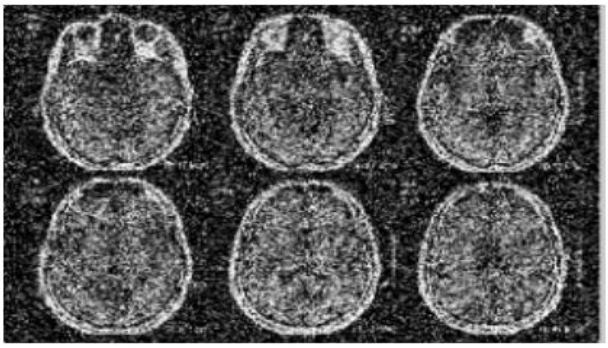


Image with Gaussian noise



De-noised image using haar wavelet

Table: Comparison of different wavelets using PSNR and MSE values

Type of wavelet	PSNR	MSE
Daubechies	53.79	0.27
Symlets	52.62	0.35
Bi orthogonal	52.16	0.39
Haar	52.78	0.34

CONCLUSION

In this paper we present an image denoising framework that adopts daubechies 9 wavelet with arithmetic coding technique to remove the noise in the image. Wavelet transform decomposes a signal into set of basic functions these basis functions are called wavelets. In this correspondence we have proposed an improved image de-noising algorithm. Due to the delivered assistant information, our presented framework is able to remove the noise in the image so that the PSNR has increased. Our presented daubechies9 wavelet with arithmetic coding method is capable in effectively restoring the image attributes which are corrupted by the noise and provides better visual quality as well. And also in our project we have used different types of wavelets like haar, symlets, bi-orthogonal.

From the above results we infer that high PSNR can be obtained through Daubechues9waveletwhencomparedtothe other wavelets.

References:

1. D.VanDeVile,M.Seghier,F.Lazeyras, T.Blu,M.Unser,WSPM: wavelet based statistical parametric mapping, Neuro image 37(2007)1205–1217.
2. E.R. McVeigh, R.M. Henkelman, M.J. Bronskill,Noise and filtration in magnetic resonance imaging,Med.Phys.12 (1985) 586–591. 3.A.O.Rodriguez,Principlesofmagnetic resonanceimaging,Rev.Mex.Fis.50(2004) 272–286.
4. P. Thunberg, P. Zeterberg, Noisedistribution in SENSE- and GRAPPA reconstructed images: a computer simulation study,Magn. Reson. Imaging 25(2007)1089–1094.
5. F.Zhang,L.Ma,MRIdenoising using thean isotropic coupled diffusion equations, in: Proceedings of IEEE 3rd International Conference on Biomedical Engineeringand Informatics, Yantai, 2010, pp. 397–401
6. J.Rajan,D.Poot,J.Juntu,J.Sijbers, Noise measurement from magnitude MRI using local estimates of variance and skewness, Phys. Med. Biol. 55 (2010)441–449.
7. J. Prinosil, Z. Smekal, K. Bartusek, Wavelet thresholding techniques in MRI domain, in: Proceedings of IEEE International Conference on Biosciences,Cancun,2010,pp.58–63.
8. H.Zhu,Y.Li,J.G.Ibrahim,X.Shi,H.An,Y.Chen,W. Gao,W.Lin,D.B.Rowe,B.S.Peterson, Regression models for identifying noise sources in magnetic

resonance imaging,J. Am.Stat.Assoc.104(2009)623–637 9.A.Wong,A.K.Mishra,Quasi-Montecarlo estimation approach for denoising MRI data based on regional statistics, IEEE Trans. BiomedicalEng.58(2011)1076–1083.

10. R.K. Kwan,A.C.Evans,G.B. Pike,MRI simulation based evaluation of image Processing and classification methods, IEEE Trans.Med.Imaging18(1999)1085–1097.