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Denoising of Magnetic Resonance Images Using Wavelet Transform

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Abstract

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique that creates detailed images of the body's organs, tissues, and physiological processes. MR images are often influenced by various noise types during acquisition and transmission, which can lead to detection and diagnostic difficulties and errors. Wavelets are mathematical tools for separating data into time-frequency components and analyzing them. Experiments show that the discrete wavelet transform families, including the Haar, Daubechies, and Symlets functions, can improve the quality of noisy images. Daubechies family is found to achieve the best results relative to the other families in terms of removing noise and preserving the details of the image.

Keywords: MRI image denoising, Wavelet toolbox, Noise reduction, Haar, Daubeches.

معـــالجة صور الرنين المغنـــاطيسي بإســـتخدام تحـــويل المـــويجات

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الخلاصة

التصوير بالرنين المغناطيسي (MRI) هو تقنية تصوير طبي غير جراحية تنتج صوراً مفصلة لأعضاء الجسم وأنسجته وعملياته الفسيولوجية. غالباً ما تتأثر صور الرنين المغناطيسي بأنواع ضوضاء مختلفة أثناء الحصول عليها ونقلها، مما قد يؤدي إلى اكتشاف صعوبات وأخطاء في الكشف والتشخيص الطبي. المويجات (Wavelets) هي أدوات رياضية لفصل البيانات إلى مكونات ذات تردد زمني وتحليلها. تظهر التجارب أن عوائل تحويل المويجات المنفصلة منها Haar, Daubechies, and Symlets يمكنها تحسين جودة الصور. وجد ان عائلة Daubechies تحقق أفضل نتائج مقارنةً بالعائلات الأخرى من حيث إزالة الضوضاء والحفاظ على تفاصيل الصورة.

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1. Introduction

The process of denoising magnetic resonance images is one of the things that needs great attention in the field of medical imaging. There are a lot of techniques that have the ability to remove noise with good image quality, but the wavelet is the most powerful of these techniques. The wavelet is used in many fields, the most important of which is the field of image compression and image denoising. This method assumes converting the original image to the wavelet space and then making corrections to the small scales of the wavelet coefficients. Usually, the discrete wavelet transformation is used for these purposes. It analyzes the image into horizontal, vertical, and diagonal elements with different levels of resolution: from large scales to small scales. Large scales contain the basic information and features of the image, while small scales are represented by small wavelet coefficients, which are affected by noise. Inverse wavelet transformation reconstructs the decomposed signal or image with its real characteristics [1,2]. In this work, we consider the case of additive Gaussian noise and then exhibit the ability of the discrete wavelet transform to improve the image and denoise it. Denoising the image can be achieved by rectification the wavelet coefficients by using soft or hard thresholding. It is very important to choose the best analysis method to achieve the best signal filtering, With a note that large decomposition coefficients are related to the signal itself. We achieve our objective by selecting the discrete wavelet transform function 2D-DWT denoising that is found to find the best signal construction.

1.1 Wavelet Transform

Wavelet transform is a mathematical tool that decomposes signals into many different frequency components. This decomposition enables the signal to be analyzed at a scale-appropriate resolution. Wavelets are signal and image representations with many resolutions. They decompose a signal into a hierarchy of scales, starting with the coarsest and working their way up to the finest [3]. A wavelet-based denoising approach typically consists of following steps:

1- Get the wavelet coefficients by transforming the original image into the wavelet domain.
2- Take the wavelet coefficients and process them. To reduce the contribution of noise in the wavelet domain, this step usually involves thresholding the wavelet coefficients.
3- To create the denoised image, apply the inverse wavelet transform or image reconstruction to the processed coefficients.

In comparison with the Fourier transform, the analyzing function of the wavelet transform can be chosen with more freedom, without the need of using sine-forms. A wavelet function ψ(t) is a small wave, which has to be oscillatory in some way to discriminate between different frequencies. The wavelet contains both the analyzing shape and the window [4].

$$\Psi(a,b)(t) = a^{\frac{-1}{2}}\Psi\left(\frac{t-b}{a}\right) \quad (1)$$

$$C(a,b) = \int_{-\infty}^{\infty} f(t)\Psi a,b(t)dt \quad (2)$$

Where A = scale control range-wide; B = position window on the time axis. Figure 1 shows a simple wavelet function [5].

1.2 Types of Noise in MR Images

Because signals never exist without noise, all digital images have some noise as a result of the corruption that arises through their acquisition and transmission due to a variety of factors. Depending on the technology used to collect or preserve medical images, they are likely to be disrupted by a complex sort of additive noise.

1.2.1 Gaussian Noise or Amplifier Noise

The Gaussian noise is added to MR image through image acquisition such as detector noise generated by low light, high temperature, transmission e.g. electronic circuit noise. The Gaussian noise has a probability density equation of the normal distribution. The probability density function (PDF) of Gaussian noise is presented in the following equation [6]:

$$p(z) = \frac{1}{\sigma 1\sqrt{2\pi}} e^{\frac{-(z1-\mu 1)^2}{2\sigma 1^2}} \quad (3)$$

Where p(z) is the Gaussian distribution equation noise in MR image; μ1 and σ1 is the mean and standard deviation respectively and z1 represents the grey level.

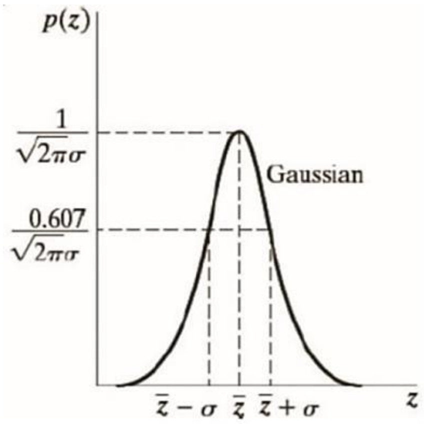

Figure -1 Gaussian Noise [6].

1.2.2 Impulsive Noise

One sort of noise that degrades the image quality is impulse noise, commonly known as salt and pepper noise. Defective pixels in camera sensors, faulty memory locations in hardware, or transmission over a noisy channel can all cause it. It is never independent and unrelated to the pixels in an MR image. In the degraded image, impulsive noise appears as white and black pixels. The following equation depicts the salt and pepper noise [6].

$$p(z) = \begin{cases} p_a & for\ z = a \\ p_b & for\ z = b \\ 0 & otherwise \end{cases} \qquad (4)$$

Where p_a , p_b are the probabilities density equation; $p(z)$ is distribution salt and pepper noise in MR image and a,b are the arrays size MR image.

1.2.3 Speckle Noise

Speckle noise is a multiplicative noise type. Any distribution is multiplied by each pixel in the image as a result of this. Synthetic Aperture Radar (SAR) images are commonly severely corrupted by this noise. Random variations the signal from an component smaller than a single image processing component effect the majority of the noise [7]. The generalized speckle model is expressed as,

$$G1(n,m) = f1(n,m) * u1(n,m) + \xi 1(n,m) \qquad (5)$$

where $G1(n,m)$ is the observed image; $f1(n,m)$ is the original image; $u1(n,m)$ is the multiplicative component of the speckle noise, and $\xi 1(n,m)$ is the additive component [7].

1.2.4 Rician Noise

Rician noise is a phenomenon that occurs naturally during the acquisition of a magnitude MRI image, making diagnosis difficult. Rician "noise" is signal-dependent, unlike additive Gaussian noise making it difficult to distinguish signal from noise. Rician noise is particularly challenging in low signal-to-noise ratio (SNR) regimes, where it not only generates random oscillations but also puts a signal-dependent bias into the data, lowering visual contrast [8].

2. Methodology

Wavelet analysis utilizes a function representation known as “wavelets” for noise filtering. Typically, the discrete form of the "wavelet transform" is employed. These functions are found as solutions for some algebraic equations and filter-bank coefficients. The technique of wavelet denoising is very effective because the wavelet transform can capture the energy of the signals in a few energy transform values. After an image is decomposed into four sub-images using wavelet transform analysis, the four sub-images are created as: approximation, horizontal details, vertical details, and diagonal details. Daubechies family of wavelets orthonormal is the most popular one among different wavelet functions. The Daubechies wavelets are indicated as “dbN”, where N denotes the order of the wavelet and db denotes the surname of Daubechies wavelet. Other wavelet families can be used in the process of noise reduction such as “Haar” and “Symlets”, with the same procedure as the db. To apply the wavelet transform for image processing, we have to implement a two-dimensional (2D) analysis and compose filter banks. To perform a 2D wavelet transform, the 1D transform is applied first across all the rows and then across all the columns at each decomposition level. Four sets of coefficients are generated at each decomposition level: “LL” as the average, “LH” as the details across the horizontal direction, “HL” as the details across the vertical direction, and “HH” as the details across the diagonal direction [1,9,10].

The denoising procedure is shown in Figure (2), which consists of several stages of the processes that are performed on the original noisy input image to get it denoised.

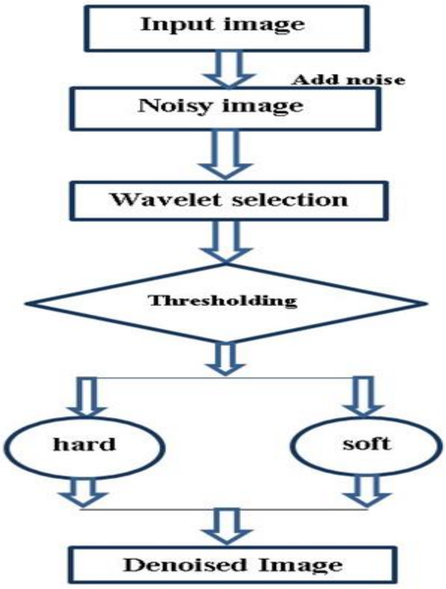

Figure -2 Denoising procedure scheme.

Each family differs from the other in several properties. The use of a family is determined by the characteristics of the image and the nature of the application.

Table 2- The wavelet families [11].

Wavelet Family Name	Wavelet Family Short Name
Haar Wavelet	Haar
Daubechies Wavelet	Db
Symbol	Sym
Coif-lets	Coif
Bi-orthogonal wavelet	Bior
Meyer wavelet	Meyr
Discrete Meyer wavelet	Dmey
Battle and Lemert’s	Btlm
Gaussian wavelet	Gaus
Mexican hat wavelet	Mexh
Morlet wavelet	Morl

3. Results and Discussion

The wavelet toolbox, which can be accessible via MATLAB's main window, is used to denoise the images in this study. By applying hard thresholding with an appropriate value. To perform the denoising process, select “apps” then “wavelet analyzer”. After bringing up the Wavelet 2- D De-noising window by clicking the De-noise button (placed in the middle right), the graphical tool creates thresholds for you automatically. Many settings are also available in the denoise interface, including thresholding type, thresholding values, and the value of sparsity and WT has many levels of decomposition. Here we use “penalize low” with three different levels. Select the option “Penalize low” from the “Select thresholding method” menu and click the “Denoise” button.

This work has investigated the WT technique in MRI images noise reduction. We have applied the noise reduction on three different MRI images head, spine, and thorax. The practical experiments showed the flexibility of discrete wavelet transform in removing the noise. From more than 200 result of denoising process with three families of Wavelet Haar, Daubechies, and Symlets, the results showed that Daubechies family provides the best filtering for MRI images. The results shown below are the best with thresholding value in the range of 60 to 75. The results of Haar wavelets in the Figures (5), (6), and (7) shows that level 3 in the Haar family gives good noise reduction results. Also, another levels are applied we chose the levels 5 and 8 to see if these levels give better results than level 3. After increasing the filtering stages, the results showed that the image is blurry. In addition many details are lost from the image. Level 3 gives the best results in the Haar family.

From the results of Daubechies wavelet denoising in the Figures (8), (9), and (10), we have noticed that level gave us the best denoising for the head. It kept the edges and the details of the image as clear as possible while removing the noise from the image. Also, level 5 is the best one in this work for the thorax part because it provided a smoother image and removed the noise without erasing its details. As a result, it’s better than level 3,8. Finally, for the spine image, level 5 gave us the best result in removing the noise and preserving as many details as possible then level 8 and the least one is level 3.

From the results of Symlet wavelet in the Figures (11), (12), and (13), we’ve noticed that Level 3 removes a small amount of noise, while level 5 removes a larger amount of noise compared to level 3. However, when the threshold value is increased, the image becomes blurry and the features are less clear, as it merged with the edges of the image. Level 8 is considered the best because it removed the largest amount of noise while preserving the features of the image and the edges are clear.

In the wavelet packet 2-D in the Figures (14) to (22), by using Haar, Daubechies, and Symlets, the results were excellent in terms of removing noise and preserving image details at almost all levels. All images used in this work were obtained from the “Dove MRI” site.

Figure -3 The original MRI images of head, spine, thorax respectively [12].

Figure -4 The noisy images with Gaussian noise.

A. The Best Results of MRI Denoising Using Wavelet 2-D

This part shows the best results of using wavelet 2-D families for head, spine, and thorax.

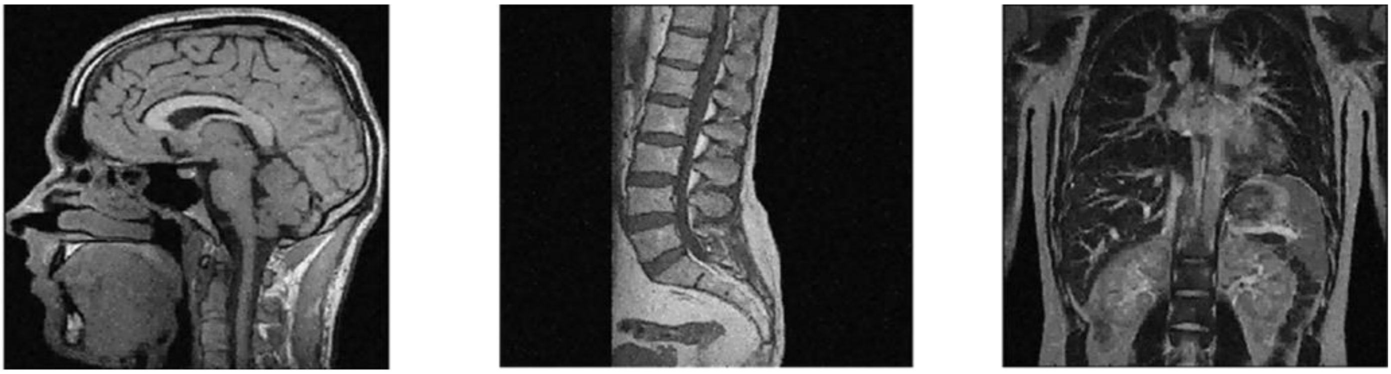

Figure -5 The MR images after Haar wavelet denoising at level 3.

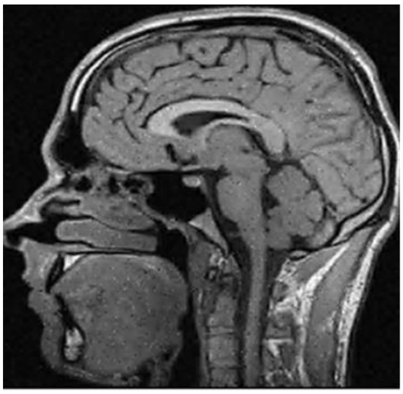

Figure -6 The head MRI image after Daubechies wavelet denoising at level 3.

Figure -7 The spine MRI image after Daubechies wavelet denoising at level 5.

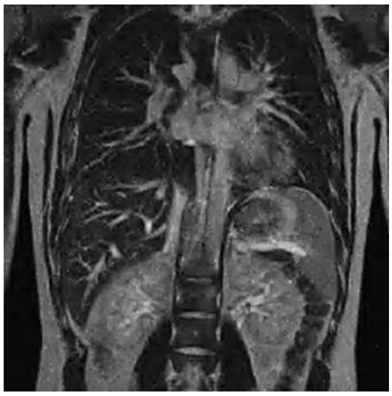

Figure -8 The thorax MRI image after Daubechies wavelet denoising at level 5.

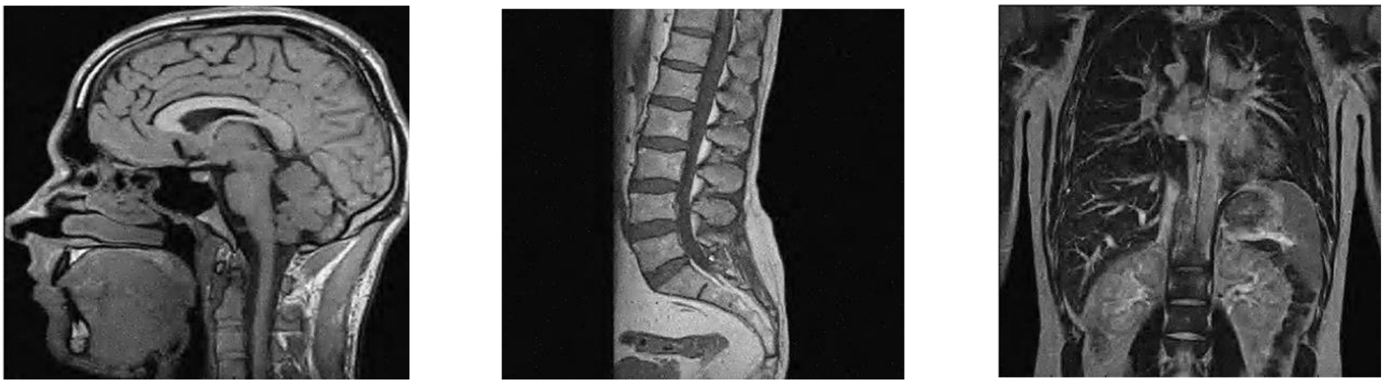

Figure -9 The MR images after Symlet wavelet denoising at level 8.

B. The Best Results of MRI Denoising Using Wavelet Packet 2-D

This part shows the best results of using wavelet packet 2-D families at level 3.

Figure -10 MRI images after Haar denoising at Level 3 with wavelet packet 2-D.

Figure -11 MRI images after Daubechies denoising at Level 3 with wavelet packet 2-D.

Figure -12 MRI images after symlet denoising at Level 3 with wavelet packet 2-D.

4.Conclusions

MRI is an effective diagnostic tool in clinical practice. The noise introduced during image acquisition reduces the ability of image interpretation. In this work, we used three different wavelets families Haar, Daubechies, and Symlet to denoise three separate MR images of three different body sections (head, spine, and thorax) in the case of additive Gaussian noise. According to the obtained results, the best result was obtained by Daubechies wavelet. Daubechies wavelet with hard thresholding introduced the best denoising results in terms of removing the noise and preserving as many details as possible.

5. Disclosure and conflict of interest

"Conflict of Interest: The authors declare that they have no conflicts of interest."

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