

# Medical Image Denoising Using Mixed Transforms

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## Abstract

In this paper, a mixed transform method is proposed based on a combination of wavelet transform (WT) and multiwavelet transform (MWT) in order to denoise medical images. The proposed method consists of WT and MWT in cascade form to enhance the denoising performance of image processing. Practically, the first step is to add a noise to Magnetic Resonance Image (MRI) or Computed Tomography (CT) images for the sake of testing. The noisy image is processed by WT to achieve four sub-bands and each sub-band is treated individually using MWT before the soft/hard denoising stage. Simulation results show that a high peak signal to noise ratio (PSNR) is improved significantly and the characteristic features are well preserved by employing mixed transform of WT and MWT due to their capability of separating noise signals from image signals. Moreover, the corresponding mean square error (MSE) is decreased accordingly compared to other available methods.

**Keywords:-** Index Terms— Denoising technique, Medical Image, Multi-wavelet Transforms, Wavelet Transform.

## الخلاصة

يقترح في هذا البحث طريقة تعتمد على خليط من التحويلات Wavelet Transform (WT) و Multiwavelet Transform (MWT) من اجل تقليل التشوه في الصور الطبية. تعتمد الطريقة المقترحة على استخدام WT و MWT بالتعاقب لتعزيز اداء ازالة التشوه من الصور الطبية. عمليا، يتم في البداية اضافة تشويه لصور الرنين المغناطيسي (MRI) والتصوير المقطعي المحوسب (CT) من اجل الاختبار. ثم تعالج الصورة المشوهة بواسطة WT لتنتج اربع تقسيمات للصورة موزعة على اساس التردد ويعالج كل تقسيم بواسطة MWT قبل مرحلة ازالة التشوه المكثفة او البسيطة. اوضحت النتائج العملية ان نسبة الاشارة الى الضوضاء (PSNR) تحسنت بشكل ملحوظ وتم المحافظة على المعلومات الاساسية للصورة. بالاضافة الى ذلك، فان متوسط نسبة الخطا انخفض تبعا لذلك بالمقارنة مع الطرق الاخرى.

**الكلمات المفتاحية:-** طرق ازالة التشويه، الصور الطبية، فلتر متعدد الموجات، فلتر احادي الموجة.

## 1. Introduction

Medical image enhancement technologies have attracted much attention since advanced medical equipments were put into use in the medical field (Sidhu *et.al.*, 2012). With the wide-spread use of digital imaging in medicine today, the quality of digital medical images becomes an important issue (Wang and Zhou, 2006). To achieve the best possible diagnoses it is important that medical images be clear and free of noise and artifacts (Wang and Zhou 2006; Arakeri and Reddy, 2011; Choubey *et.al.*, 2011; Mitiche *et.al.*, 2013). Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because qualities of medical images are often deteriorated by noise and other data acquisition devices, illumination conditions, etc (Sidhu *et.al.*, 2012 ; Deepa and Sumithra, 2015). Medical image denoising must preserve more details than the general denoising task do since doctors rely on these details to obtain correct diagnosis. Although many efforts have been done in medical image denoising, it is still a challenge now even

for some well-known filters (Liao *et.al.*, 2010). The mixed transform filter is one of these.

To achieve the best possible diagnosis it is important that medical images be free of noise and thus preprocessing is one of the important task in medical image processing(Wang and Zhou, 2006; Arakeri and Reddy, 2011; Mitiche *et.al.*, 2013; Choubey *et.al.*, 2011; Sukanesh, 2013). Therefore, various methods have been proposed as solutions to the so-called image denoising problem, which in our context consists of reducing noise in the CT image domain. The simplest ones are based on linear filtering using temporal or spatial low-pass filters. The major drawback of these methods is that apart from noise reduction they also cause increased blurriness and hence a reduction of signal information. High-pass filters such as Ramp (Lyra and Ploussi, 2011; Adamidi *et. al.*, 2013).

At present, image denoising methods can be mainly divided into two categories: spatial domain denoising and transform domain denoising. The spatial-domain denoising methods include median filter (Mohan *et.al.*, 2015), Weiner filter (Khare and Tiwary, 2006, Deepa and Sumithra, 2015; Jain, 2015), Bilateral filter (Tomasi and Manduchi 1998), etc. These methods can reduce noise to a reasonable extent but make the image blurring. Transform-domain denoising methods include wavelet (Yue *et.al.*, 2006; Rabbani *et.al.*, 2009), curvelet (Sivakumar, 2007), contourlet (Satheesh and Prasad, 2011), etc. These methods have an excellent ability to remove noise. However, they cannot preserve the local image features well (Bai *et.al.*, 2016).

The most widely used techniques for denoising in image processing are wavelet transform based hard and soft thresholding (Kishore *et.al.*, 2015).

Wavelet-based coding provides substantial improvements in pictures quality at higher denoising. Over the past few years, a variety of powerful and sophisticated wavelets-based schemes for images denoising, have been developed and implemented. For better performances in denoising, filters used in wavelets transforms should have the property of orthogonality, symmetry, shorter supported and higher approximations order. Due to implementations constraints scalars wavelets do not satisfy all these properties simultaneously. A new classes of wavelets called 'multi-wavelets' which possess more than one scaling filter may overcome these problems. This multi-wavelet offered the possibility of a better performance and higher degrees of freedom for images processing's applications, than those gotten in with scalar wavelets. Multi-wavelets can achieve a level of performance superior to that of scalar wavelets with similar computationally complexity (Liao *et.al.*, 2010).

This paper is organized as follows: section II describes the denoising techniques, WT, and MWT. Section III presents the proposed mixed transform of medical images. Section IV describes performance measurements of images denoising and standard metric to measure the quality of reconstructed images. Section V discusses the results and the simulation of the proposed mixed transform. Finally, section VI sums up the conclusions of the study.

## 2. Denoising Techniques

Transforms coding is one of the important techniques used in denoising techniques. Mixed transform method used here is proposed based on a combination of WT and MWT in a sequence manner to reduce noise and preserve the image details. The main goal of

any denoising techniques is to remove noise without too much loss of original data (Khalaj and Naimi, 2009).

### A. Discrete Wavelet Transform

The 2-D wavelet decomposition of an image is performed by applying 1-D Discrete Wavelet Transform (DWT) along the rows and then along the columns. At first, 1-D DWT is applied along the rows of the input image. This is called row-wise decomposition (Yue *et.al.*, 2006). Then, 1-D DWT is applied again along the columns of the resultant image. This is called column-wise decomposition. The inner products of the individuals wavelets  $\psi(j, k)$  are equal to zero. To this end, dilation factors are chosen to be powers of 2. For DWT, the set of dilation and translation of the mother wavelet is defined as (Alhanjouri, 2011):

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \quad (1)$$

Where  $j$  is the scaling factor and  $k$  is the translation factor. It is obvious that the dilation factor isn't a power of 2. Forward and inversed transforms are then calculated using the following equations (Alhanjouri, 2011).

$$C_{\tau,s} = \int_{-\infty}^{+\infty} f(t) \psi_{\tau,s}(t) dt \quad (2)$$

$$f(t) = \sum_{\tau,s} C_{\tau,s} \psi_{\tau,s}(t) \quad (3)$$

For efficient décor-relations of the data, analysis, wavelets sets  $\psi(j, k)$  which match the features of the data should be chosen. This together with orthogonally of the wavelet sets will result in a series of sparse coefficients in the transform domains, which obviously will reduce the amounts of bits needed to encode data (Mitiche *et.al.*, 2013).

This operation results in four decomposed sub-band images referred to as low– low (LL), low–high (LH), high–low (HL), and high–high (HH). For multi resolution analysis, the LL band of previous level is again decomposed by DWT. Figures 1 (a) and (b) show the original image and respectively the wavelet transformed image at level 1.

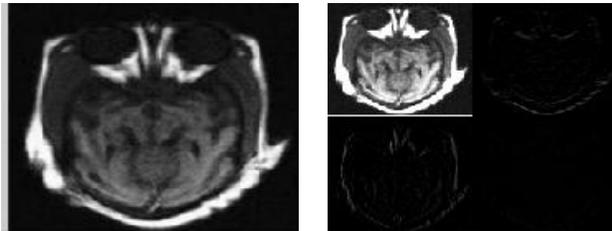


Figure (1) (a) Sample Medical Image (b) Dwt Image At Level 1

### B. Multi-Wavelet Transform

Multi-wavelets have been introduced as more powerful multi-scales analysis tools. A scalar wavelets system is based on a single scaling functions and mother wavelets. On the other hand, a multi-wavelet uses several scaling functions and mother wavelets. Multi-wavelets, namely, vector-valued wavelets functions, are not a new addition to the

classical wavelets theory that has revealed to be successfully in practical applications, such as signals and images compressions. In fact, multi-wavelets possess several advantages in comparisons to scalar wavelets, since a multi-wavelets system can simultaneously provide perfect reconstructions while preserving orthogonality, symmetry, a higher order of approximations (vanishing moments), etc. Nevertheless, multi-wavelets differ from scalar wavelet systems in requiring two or more input streams to the multi-wavelet filter bank (Kishore *et.al.*, 2015).

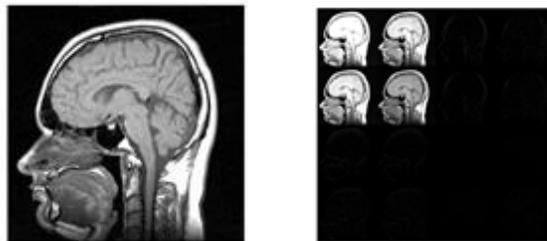
The multi-wavelet ideas are originated from the generalization of scalar wavelets; instead of one scaling function and one wavelet, multiple scaling functions and wavelets are used. This leads to more degrees of freedom in constructing wavelets. Therefore, opposed to scalar wavelets, properties, which aren't fundamentals in signals processes, such as compacted supports, orthogonality, symmetry, vanishing moments, and short supporting can be gathered simultaneously in multi-wavelets. The increase in the degrees of freedom in multi-wavelets is obtained at the expense of replacing scalars with matrices, scalar functions with vectors functions and singles mattresses with a block of matrices. Also, prefiltering is an essential task which should be performed for any uses of multi-wavelet in the signals processing (Al-Sammaraie, 2011).

Many types of multi-wavelets such as Geronimo-Hardin Massopust (GHM) and Chui-Lian (CL) multi-wavelets have been developed (Xia *et.al.*, 1996). To implement the multi-wavelets transforms, a new filter bank structure is required where the low-pass and high-pass filters banks are matrices rather than scalars. That is, the GHM two scaling and wavelet functions satisfy the following two-scale dilation equations (Xia *et.al.*, 1996).

$$\begin{bmatrix} \phi_1(t) \\ \phi_2(t) \end{bmatrix} = \sqrt{2} \sum_k H_k \begin{bmatrix} \phi_1(2t - k) \\ \phi_2(2t - k) \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \sqrt{2} \sum_k G_k \begin{bmatrix} \psi_1(2t - k) \\ \psi_2(2t - k) \end{bmatrix} \quad (5)$$

The (2×2) matrix filters in the multi-wavelet filter bank requires vector inputs. Thus, a 1-D inputs signals must be transformed into two 1-D signals. This transformation is called preprocessing. For some multi-wavelets, the preprocessing must be accompanied by an appropriate prefiltering operations that depend on the spectral characteristics of the multi-wavelets filters (Xia, 1998). Figure 2 (a) shows the original image and Figure 2 (b) shows the wavelet transformed image at level 1.



**Figure (2) (a) Sample Medical Image (b) MWT Image At Level 1**

### 3. Proposed Method

The method consists mainly of applying the multi-wavelet and wavelet transform in a cascaded manner to the MRI image or medical data. The mixed transform is analyzed for denoising the medical images corrupted by Gaussian noise. The medical image is taken as an input and AWGN is generated randomly and added to the medical image. Thereby, the proposed transform is implemented by applying MWT first, this in turn introduces the four approximation bands (L1L1, L1L2, L2L1 and L2L2) which have approximated information to the original signal, (L1H1, L1H2, L2H1 and L2H2), (H1L1, H1L2, H2L1 and H2L2), and (H1H1, H1H2, H2H1 and H2H2). The four square approximated bands results are splits and each one is processed individually.

The description of the procedure used in the denoising process for method transform schemes, is as follows: Step.1 Applying the WT to the approximation band (L1L1, L1L2, L2L1 and L2L2) which results four square sub-bands as shown in Figure 3.

The noise is removed by applying soft thresholding and hard thresholding to the frequency sub-bands of DWT.

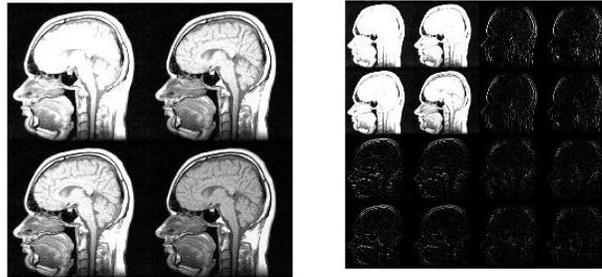


Figure (3) (a) The Approximation Band (LL) (b) WT Image at Level 1

Step.2 Repeat step.1 by applying the WT to the approximated bands (L1H1, L1H2, L2H1 and L2H2), (H1L1, H1L2, H2L1 and H2L2), and (H1H1, H1H2, H2H1 and H2H2) and then the noise is removed by applying soft thresholding and hard thresholding to the frequency sub-bands of DWT. Figure 4 shows the block diagram of the proposed method.

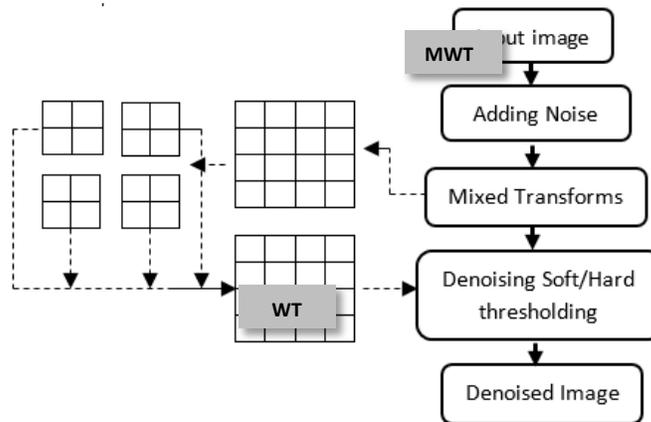


Figure (4): Block Diagram of Proposed Method

#### 4. Performance Measurements

Evaluation of images denoising methods need a standard metric to measure the quality of reconstructed images compared with the originals ones. A common measure used for this purpose is the peak signal to noise ratio (PSNR). It has only a limited and approximated relationship with the perceived errors noticed by the human visual systems. Denoting the pixels of the original images by  $x(n)$  and the pixels of the reconstructed image from  $\bar{x}(n)$ , the mean square error (MSE) between the two images is defined as (Ruchika and Singh, 2012):

$$MSE = \frac{1}{N} \sum_{i=1}^N (x(n) - \bar{x}(n))^2 \quad (6)$$

The root mean square error (RMSE) is defined as the square root of the MSE, therefore the PSNR is defined as (Al-Sammaraie, 2011):

$$PSNR = 20 \log \frac{\max |x(n)|}{RMSE} \quad (7)$$

The absolute value is normally not needed, since pixel values are rarely negatives. The PSNR is dimensionless, since the units of both numerator and denominator are pixel values. However, because of the uses of the logarithms, the PSNR is expressed in decibel (dB).

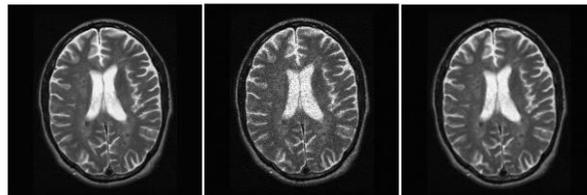
The simulation results of the proposed algorithms are obtained using a MATLAB (R2014a). It is used to run on a PC with 2.3 GHz processor, 500 GB hard disk with 4 GB main memory.

#### 5. Results and Discussion

The experimental results of the MRI image denoising using the proposed mixed transforms algorithms are shown in Figure 5.



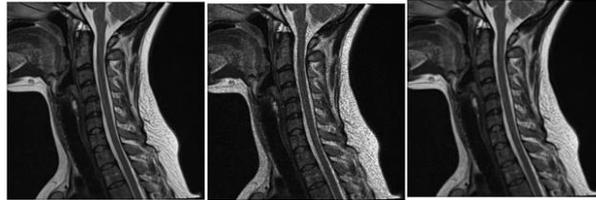
(a)



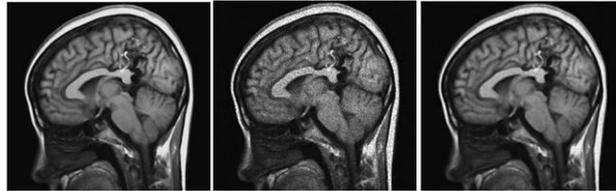
(b)



(c)



(d)



(e)



(f)

**Figure (5) : (1) Input Image (2) Noisy Image (3) Denoising Image**

Here, different medical images were used, each image contains different information relative to the other image so different results were obtained. Table (1) shows the results for medical images in Figure (5) using the proposed method.

**Table 1 MSE and PSNR for Proposed Method for Different MRI Images**

<i>Images</i>	<i>Before Denoising</i>		<i>After Denoising</i>	
	<i>MSE</i>	<i>PSNR</i>	<i>MSE</i>	<i>PSNR</i>
<i>a</i>	1.16	12.3	0.71	14.46
<i>b</i>	1.28	12.61	0.68	15.37
<i>c</i>	0.59	13.39	0.35	15.55
<i>d</i>	0.63	12.46	0.39	14.64
<i>e</i>	0.74	12.25	0.42	14.64
<i>f</i>	1.3	13.98	0.95	15.33

This method can also be compared with other methods such as WT and MWT. Table (2) shows the results of the proposed method relative to other methods for image (a) in Figure 5

**Table 2 MSE and PSNR for Different Methods for MRI Image Denoising**

<i>Algorithm</i>	<i>Before Denoising</i>		<i>After Denoising</i>	
	<i>MSE</i>	<i>PSNR</i>	<i>MSE</i>	<i>PSNR</i>
<i>Wavelet Transform</i>	1.15	12.3	0.88	13.5
<i>Multiwavelet Transform</i>	1.16	12.31	0.77	14.09
<i>Mixed Transform</i>	1.16	12.3	0.71	14.46

It is noticeable that the MSE for the proposed method is less than those for the wavelet transform and the multiwavelet transform, while PSNR for proposed method is higher than those for the other methods which means the proposed method achieve a better resolution than the other methods.

## 6. Conclusion

A proposed method has been developed for efficient medical image denoising based on MWT transform and WT transform, which are employed in a different distribution. This distribution was exploited by the cascading manner. The proposed method offers a better denoising performance for medical image than that for the wavelet transform and multiwavelet transform. Extensive simulations confirm the improvement in denoising performances offered by the proposed mixed transform over a single transform. Sample results are presented to illustrate the improvement.

## Abbreviations

The following abbreviations are used in this manuscript:

- CT Computed Tomography
- MRI Magnetic Resonance Imaging
- 1-D One – Dimensional
- 2-D Two – Dimensional
- DWT Discrete Wavelet Transform
- LL Low Low Subband
- HL High Low Subband
- LH Low High Subband
- HH High High Subband
- GHM Geronimo-Hardin-Massopust
- CL Chui-Lian
- MWT Multiwavelet Transform
- PSNR Peak Signal to Noise Ratio
- MSE Mean Square Error
- RMSE Root Mean Square Error

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