CHAPTER 4

WAVELET IMAGE DENOISING

Over the past decade, there has been a new and significant contribution to the image processing literature, which lies in the development of wavelet-based methods for the purpose of image denoising. Basic wavelet image restoration techniques are based on thresholding in the sense that each wavelet coefficient of the image is compared to a given threshold; if the coefficient is smaller than the threshold, then it is set to zero, otherwise it is kept or slightly reduced in magnitude. Multi-scale analysis has been found particularly successful for image de-noising and enhancement problems given that a suitable separation of signal and noise can be achieved in the transform domain (i.e. after projection of an observation signal) based on their distinct localization and distribution in the spatial-frequency domain. In this chapter, various wavelet thresholding methods for the purpose of image denoising will be studied and implemented in order to assess and compare their performance.

4.1 WAVELET DENOISING ALGORITHM

The discrete wavelet transform translates the image content into an approximation subband and a set of detail subbands at different orientations and resolution scales. Typically, the band-pass content at each scale is divided into three orientation subbands characterized by horizontal, vertical and diagonal directions. The approximation subband consists of the so-called scaling coefficients and the detail subbands are composed of the wavelet coefficients. In the detail subbands HLi, LHi and HHi, the brightest color
represents large positive values of the wavelet coefficients and the dark color corresponds to the negative coefficient values with largest magnitudes (Motwani et al 2004). Several properties of the wavelet transform, which make this representation attractive for denoising are

- multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- sparsity - the majority of the wavelet coefficients are small in magnitude
- edge detection - large wavelet coefficients coincide with image edges
- edge clustering - the “edge” coefficients within each subband tend to form spatially connected clusters
- edge evolution across scales - the coefficients that represent image edges tend to persist across the scales

Figure 4.1 Wavelet Denoising Procedure.
Figure 4.1 shows the wavelet denoising procedure for an image. Wavelets have been used for denoising in many medical imaging applications (Gauangmin et al 2003). A general procedure is (i) calculate the discrete wavelet transform; (ii) remove noise from the wavelet coefficients and (iii) reconstruct a denoised signal or image by applying the inverse wavelet transform. The scaling coefficients are typically not modified except for some special imaging modalities like MR. The noise-free component of a given wavelet coefficient is typically estimated by wavelet shrinkage (Motwani et al 2004) the idea of which is to heavily suppress those coefficients that represent noise and to retain the coefficients that are more likely to represent the actual signal or image discontinuities.

Let \( w_{k,j}^D \) represent the wavelet coefficient at the resolution scale \( 2^j \) (\( 1 \leq j \leq J \)), spatial position \( k \) and orientation ‘\( D \)’. For compactness, we shall omit the indices that denote the scale and the orientation unless in cases where it is explicitly needed. Assume that in each wavelet subband an additive noise model holds

\[
w_k = y_k + n_k
\]

(4.1)

where \( y_k \) is the unknown noise-free signal component and \( n_k \) an arbitrary noise contribution. A majority of the wavelet shrinkage estimators can be represented as

\[
\hat{y}_k = R_k w_k, \quad 0 \leq R_k \leq 1
\]

(4.2)

where \( R_k \) denotes a shrinkage factor. Ideally, \( R_k \) should be close to zero when \( w_k \) is likely to represent pure noise and it should be close to one when \( w_k \) is likely to represent a true signal or image discontinuity. For the classical wavelet thresholding rules (Chang et al 2005) a threshold value \( T \) is defined and \( R_k = 0 \) is specified as follows. For hard thresholding \( R_k = 0 \) if
$|w_k| < T$ and $R_k = 1$ if $|w_k| \geq T$. For soft thresholding $R_k = 0$ if $|w_k| < T$ and $R_k = 1 - T$ if $|w_k| \geq T$. One of the first soft thresholding methods was developed within medical imaging, for the noise reduction in magnetic resonance images.

### 4.1.1 Thresholding operators for de-noising

In wavelet domain the small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information. As a general rule, wavelet coefficients with larger magnitude are correlated with salient features in the image data. In that context, de-noising can be achieved by applying a thresholding operator to the wavelet coefficients (in the transform domain) followed by reconstruction of the signal to the original image (spatial) domain (Donoho 2003).

Typical threshold operators for de-noising include hard thresholding:

$$
\rho_T(x) = \begin{cases} 
  x, & |x| > T \\
  0, & |x| \leq T
\end{cases} \quad (4.3)
$$

soft thresholding (wavelet shrinkage) (Donoho 2004)

$$
\rho_T(x) = \begin{cases} 
  x - T, & x \geq T \\
  x + T, & x \leq -T \\
  0, & |x| < T
\end{cases} \quad (4.4)
$$

and affine(firm) thresholding

$$
\rho_T(x) = \begin{cases} 
  x, & |x| \geq T \\
  2x + T, & -T \leq x \leq T / 2 \\
  2x - T, & |T / 2| \leq x \leq T \\
  0, & |x| < T
\end{cases} \quad (4.5)
$$
The shapes of these thresholding operators are illustrated in Figure 4.2.

(a) Hard thresholding        (b) Soft thresholding         (c) Affine thresholding

Figure 4.2 Example of thresholding functions,

4.1.2 Selection of Threshold Value

Given the basic framework of de-noising using wavelet thresholding as discussed in the previous sections, it is clear that the threshold level parameter $T$ plays an essential role in denoising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal. Paying too much attention to smoothness, however, destroys details and in image processing may cause blur and artifacts. There are a variety of ways to determine the threshold value $T$ as we will discuss in this section.

Depending on whether or not the threshold value $T$ changes across wavelet scales and spatial locations, the thresholding can be:

1. **Global Threshold**: a single value $T$ is to be applied globally to all empirical wavelet coefficients at different scales. $T = \text{const}$
2. **Level-Dependent Threshold**: a different threshold value \( T \) is selected for each wavelet analysis level (scale). \( T = T(j), \ j = 1, \ 2, \ …, \ J \) \( J \) is the coarsest level for wavelet expansion to be processed.

3. **Spatial Adaptive Threshold**: the threshold value \( T \) varies spatially depending on local properties of individual wavelet coefficients. Usually, \( T \) is also level-dependent. \( T = T_j(x, y, z) \).

While a simple way of determining \( T \) is a percentage of coefficients maxima, there are different adaptive ways of assigning the \( T \) value according to the noise level (estimated via its variance \( \sigma \)):

1. **Universal Threshold**: \( T = \sigma \sqrt{2 \log n} \), with \( n \) equal to the sample size. This threshold was determined in an optimal context for soft thresholding with random Gaussian noise. This scheme is very easy implement, but typically provides a threshold level larger than with other decision criteria, therefore resulting in smoother reconstructed data. Also such estimation does not take into account the content of the data, but only depends on the data size. \( n \)

2. **Minimax Threshold**: \( T = \sigma T_n \) where is determined by a minimax rule such that the maximum risk of estimation error across all locations of the data is minimized. This threshold level depends on the noise and signal relationships in the input data. \( nT \)

3. **Stein Unbiased Estimated of Risk (SURE)**: Similar as minimax threshold but is determined by a different risk rule.
4. **Spatial Adaptive Threshold**: \[ T = \frac{\sigma^2}{\sigma_x} \] (Xu et al 2005), where \( \sigma_x \) is the local variance of the observation signal, which can be estimated using a local window moving across the image data or, more accurately, by a context-based clustering algorithm.

In many automatic de-noising methods to determine the threshold value \( T \), an estimation of the noise variance \( \sigma \) is needed. Donoho and Johnstone (Donoho 2005) proposed a robust estimation of noise level \( \sigma \) based on the median absolute value of the wavelet coefficients as:

\[
\sigma = \frac{\text{median}(|W_i(x, y, z)|)}{0.6745}
\]  

(4.6)

where \( i \) is the most detailed level of wavelet coefficients. Such estimator has become very popular in practice and is widely used.

### 4.2 WAVELET-BASED RICIAN NOISE REMOVAL

The objective of this technique is to develop a filtering method to estimate the signal from the magnitude image data. It is well known that magnetic resonance magnitude image data obey a Rician distribution. Unlike additive Gaussian noise, Rician noise is signal-dependent, and separating signal from noise is a difficult task. Rician noise is especially problematic in low signal-to-noise ratio (SNR) regimes where it not only causes random fluctuations, but also introduces a signal-dependent bias to the data that reduces image contrast. This scheme of wavelet-domain filtering methods for Rician noise removal adapts to variations in both the signal and the noise.

Magnetic resonance magnitude image data are usually modelled by the Rician distribution (Weaver et al 2004). The term Rician noise is used to
refer to the error between the underlying image intensities and the observed data. Rician noise is not zero-mean, and the mean depends on the local intensity in the image. Because of this complication, magnetic resonance image estimation from noisy data is especially challenging.

This novel wavelet-domain filtering procedure overcomes this difficult estimation problem. Unlike previously proposed methods for MR estimation based on wavelet coefficient soft thresholding and related thresholding methods (Berkner et al. 2004), this new approach explicitly accounts for the Rician nature of the data. The new procedure reduces the Rician noise, while preserving the key image details and features. It is shown that the new wavelet-domain filter performs better than a standard wavelet method in low SNR conditions.

At high SNR, the Rician distribution is well-approximated as Gaussian. For example, if the SNR in a pixel is greater than 10 dB, then the mean pixel value is more than three standard deviations from the origin and the Rician distribution is approximately Gaussian. If the SNR is below 10 dB, then the Rician distribution deviates from Gaussian. Hence, in high SNR regimes the MRI data can be viewed as corrupted by additive Gaussian white noise with standard deviation $\sigma$, and consequently separation of signal and noise is fairly straightforward in the wavelet-domain. To derive a wavelet-domain filter for high SNR MR, let us assume that the noise in the MR magnitude image is additive white Gaussian noise with standard deviation $\sigma$. Based on this assumption and the fact that DWT is an orthogonal transformation, the variance in each wavelet coefficient is also $\sigma^2$. Hence, one can filter according to $\sigma_i \left( \frac{d^2 - 3\sigma_i^2}{d_i^2} \right)$ with $\hat{\sigma}_i^2 = \sigma^2$ (a constant).
4.2.1 Squared Magnitude Image Algorithm

1) Compute the J-scale DWT of the squared magnitude image.

2) Form estimates of the variances \( \sigma_i^2 \) of each wavelet coefficient

\[
\hat{\sigma}_i^2 = 4\sigma^2 \max \left[ \sum_m \psi_i^2[m]x^2[m] \right] - \sigma^2, \sigma^2
\]

3) Filter the wavelet coefficients according to

\[
\sigma_i = \left( \frac{d_i^2 - 3\sigma_i^2}{d_i^2} \right)
\]

4) Remove the bias from the scaling coefficients by subtracting

\[
C = 2^{J+1}\sigma^2
\]

from each, where \( \sigma^2 \) is an estimate of the underlying complex Gaussian noise variance.

5) Compute the inverse DWT of the filtered wavelet and scaling coefficients to obtain an estimate of variance.

6) Take the pixel-by-pixel square-root of the result to obtain an estimate of \( \sigma \).

4.2.2 Experimental Result

In this experiment, the Haar wavelet is employed. In all experiments, the noise variance \( \sigma^2 \) was estimated and the shift-invariant filtering scheme with \( K=2 \) based on the \( J=2 \) scale Haar DWT was used.

Example 1: MRI Data

Here, the performance of the filtering algorithms is examined with real MRI data. To simulate a low SNR MR image with a known “truth” we have taken a high SNR image, added complex Gaussian white noise \( \sigma^2 = 256 \) to it, and computed its magnitude. The resulting image is a low
SNR MR image with a Rician distribution. The noise level was chosen so that the resulting image was similar to low SNR levels encountered in practice. In this case, the SNR in the low intensity (gray matter) region of the brain is approximately 6 dB. The high and low SNR images are shown in Figure 4.3 (a) and 4.3(b), respectively.

![High SNR MR brain image](image1.png)  ![Simulated low SNR image with Rician noise](image2.png)  
![Filtered image using Wiener filter](image3.png)  ![Filtered image using wavelet](image4.png)

Figure 4.3 Wavelet-domain filtering to improve low SNR MR Image

**Example 2: Low SNR MRI Data**

The performance of the filtering algorithms is tested here with actual low SNR MRI data. Figure 4.4 shows the original and filtered images. The noise power was estimated from the mean pixel value in the regions of
the squared magnitude image outside the patient’s head. The SNR in the low intensity regions of the brain is approximately 9 dB. Both algorithms again significantly reduce random fluctuations due to noise without loss of image detail.

The region of interest (ROI) indicated by the highlighted rectangle in Figure 4.4 (b) is used to assess the contrast of the two filtered images. The contrast in the images is computed by \( c = \frac{m_1 - m_2}{m_1 + m_2} \), where \( m_1 \) is the mean pixel value in the bright region running down the middle of the ROI, and \( m_2 \) is the mean pixel value in the background of the ROI. In this case, the contrast in the ROI is roughly 11% better in the result of wavelet compared to Wiener.

![Figure 4.4 Filtering low SNR MR Image](image)

(a) Low SNR MR brain image  
(b) Region of interest (ROI) for contrast comparisons  
(c) Filtered image using Wiener filter  
(d) Filtered image using wavelet

**Figure 4.4 Filtering low SNR MR Image**
4.3  ADAPTIVE MULTISCALE PRODUCTS THRESHOLDING

Edge-preserving denoising is of great interest in the restoration process of MR images. In wavelet-based multiscale products thresholding scheme for noise suppression of magnetic resonance images a Canny edge detector-like dyadic wavelet transform is employed (Zaroubi et al 2006). This results in the significant features in images evolving with high magnitude across wavelet scales, while noise decays rapidly. To exploit the wavelet interscale dependencies we multiply the adjacent wavelet subbands to enhance edge structures while weakening noise. In the multiscale products, edges can be effectively distinguished from noise. Thereafter, an adaptive threshold is calculated and imposed on the products, instead of on the wavelet coefficients, to identify important features. Experiments show that the proposed scheme better suppresses noise and preserves edges than other wavelet-thresholding denoising methods.

Suppose $f(x,y)$ is a 2-D measurable and square-integrable function such that $f \in L^2(\mathbb{R}^2)$. The wavelet transform of $f(x,y)$ at scale $\cdot s$ and position $(x,y)$ has two components (Alexander 2006)

\[
W_s^x f(x,y) = f \ast \psi_s^x(x,y) \quad (4.7)
\]

and

\[
W_s^y f(x,y) = f \ast \psi_s^y(x,y) \quad (4.8)
\]

The two components of multiscale products for 2D images are

\[
P_j^x f(x,y) = W_j^x f(x,y) \cdot W_{j+1}^x f(x,y) \quad (4.9)
\]

and

\[
P_j^y f(x,y) = W_j^y f(x,y) \cdot W_{j+1}^y f(x,y) \quad (4.10)
\]
The canny edge detector-like wavelet transform can be developed as follows. Suppose $\theta(x,y)$ is a 2-D differentiable smooth function whose integral is equal to 1 and converges to 0 at infinity. For example $\theta(x,y)$ could be the tensor product of one-dimensional (1-D) smooth functions: $\theta(x,y) = \theta(x) \cdot \theta(y)$. We define the two wavelets $\psi^x(x,y)$ and $\psi^y(x,y)$ at horizontal and vertical directions as

$$
\psi^x(x,y) = \frac{\partial \theta(x,y)}{\partial x}, \quad \psi^y(x,y) = \frac{\partial \theta(x,y)}{\partial y}
$$

(4.11)

In this new de-noising scheme, the adaptive multiscale products thresholding, the merits of the thresholding technique and wavelet interscale dependencies are merged (Pizurica et al 2003). A significant wavelet coefficient $\hat{W}_j^d f(x,y)$ where $d = x, y$, indicates $x$ or $y$ dimension, is identified if its corresponding multiscale products value $P_j^d f(x,y)$ is greater than an adaptive threshold $t_p^d(j)$.

The algorithm is summarized as follows.

1) Compute the DWT of input image up to $J$ scales.

2) Calculate the multiscale products $P_j^d f(x,y)$ and preset the thresholds $t_p^d(j)$. Then threshold the wavelet coefficients by

$$
\hat{W}_j^d f(x,y) = \begin{cases} 
W_j^d f(x,y) & P_j^d f(x,y) \geq t_p^d(j) \\
0 & P_j^d f(x,y) < t_p^d(j) 
\end{cases}
$$

(4.12)
3) Recover the image from the thresholded wavelet coefficients
\[ \hat{W}_j^x f(x, y) \] and \[ \hat{W}_j^y f(x, y) \]

4.3.1 Experimental Results

The performances by this scheme on some MR images are compared with those of the soft thresholding scheme (STH), BayesShrink and the hard thresholding scheme (HTH) (Sadler et al 2006). Thus, we implement the two schemes with the over-complete wavelet expansion (OWE). The residual noise is better smoothed and the artifacts are attenuated. The wavelet employed in the STH and HTH schemes is the compactly supported orthogonal wavelet of Daubechies with four vanishing moments (Coifman et al 2007). The constant appearing in the threshold of the scheme HTH is set at 3.1. The proposed scheme is referred as MPTH. The MR images in our experiments are 512 x 512 in size and the decomposition level is four.

Figure 4.5(a) is a noisy MR image Liver. The DROI and UROI used for calculating the MSR and CNR indexes are highlighted. Denoised images by the three schemes are illustrated in Figure 4.5 (b)–(d), respectively, and the MSR and CNR values are listed in Table 4.1. The presented algorithm MPTH achieves the highest quantity measurements. Notice that the denoised image by the STH contains a few stains and the result by the HTH retains much noise (if the threshold of the HTH is set higher to suppress noise, the estimated image would be over-smoothed). The MPTH preserves edges better and yet effectively removes noise.
Table 4.1 MSR and CNR results of liver MR image

<table>
<thead>
<tr>
<th>Method</th>
<th>DROI 1</th>
<th>DROI 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CNR</td>
<td>MSR</td>
</tr>
<tr>
<td>Original</td>
<td>2.61</td>
<td>2.61</td>
</tr>
<tr>
<td>STH</td>
<td>4.08</td>
<td>5.53</td>
</tr>
<tr>
<td>HTH</td>
<td>4.10</td>
<td>5.58</td>
</tr>
<tr>
<td>MPTh</td>
<td>4.31</td>
<td>5.98</td>
</tr>
</tbody>
</table>

Figure 4.5 Denoising of liver MR image
Another experiment on an MR image Spine is illustrated in Figure 4.6. The MSR and CNR measurements are listed in Table 4.2. The results showed in Figure 4.6(b) and 4.6(c) appear to be veiled by the residual noise.

Table 4.2 MSR and CNR results of spine MR images

<table>
<thead>
<tr>
<th>Method</th>
<th>DROI 1</th>
<th>DROI 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CNR</td>
<td>MSR</td>
</tr>
<tr>
<td>Original</td>
<td>2.26</td>
<td>1.79</td>
</tr>
<tr>
<td>STH</td>
<td>2.96</td>
<td>2.75</td>
</tr>
<tr>
<td>HTH</td>
<td>2.98</td>
<td>2.78</td>
</tr>
<tr>
<td>MPTH</td>
<td>3.10</td>
<td>2.91</td>
</tr>
</tbody>
</table>

Figure 4.6 Denoising of spine MR image
This scheme of MR image denoising is using an adaptive wavelet thresholding technique. Unlike many traditional schemes that directly threshold the wavelet coefficients, this scheme multiplies the adjacent wavelet subbands to amplify the significant features and then applies the thresholding to the multiscale products to better differentiate edge structures from noise. The distribution of the products was analyzed and an adaptive threshold was formulated to remove most of the noise. Experiments on the MR images show that the proposed scheme not only achieves high MSR and CNR measurements but also preserves more edge features.

4.4 CONTEXT MODELING DENOISING

We present an adaptive neighborhood selection algorithm by accounting for the spatial context information, calculated in the undecimated wavelet domain. A modified Wiener filter is approached by a novel bivariate thresholding, considering local signal variance by valid information from the selected neighborhood windows. This scheme can preserve edges more effectively while suppressing noise and artifacts; moreover, both the SNR and RMSE are improved obviously.

The MR magnitude images are considered to be governed by a Rician distribution, having a signal dependent mean. Nowak (Nowak 2000) advanced a wavelet-domain Wiener-like filtering in the squared magnitude images, of which the noise was noncentral chi-square distributed. His work apparently reduces the Rician noise and removes the bias in the data. More recently, the spatial dependency of the wavelet coefficients across adjacent scales in the form of multiscale products was developed (Bao et al 2003). Although the idea is simple, the calculation of interscale correlation is often influenced by the tiny excursion of coefficients along the temporal axes. Pizurica (Pizurica et al 2003) proposed an empirical estimation of the statistical distributions of the coefficients combining these multiscale
products, while using a wavelet domain indicator of the local spatial activity. An improved estimation method in the undecimated wavelet domain is discussed here, providing an adaptive neighbourhood windows’ selection and a reformative MMSE filter—bivariate Wiener filter.

The integrated thresholding method can be described as follows:

i) Compute the UWT of the complex MR image;

ii) Use equations (4.13), (4.14) and (4.15) to find a rationally maximal window around the current concerned coefficient;

\[
\text{Re}_{p,q} = \text{real}(d(p,q)), \quad \text{Im}_{p,q} = \text{imag}(d(p,q)) \quad p,q \in \mathbb{Z}_+ \quad (4.13)
\]

\[
\text{Corr}(u,v) = \left[ \frac{\text{Re}_{u,v} - \text{Re}_{i,j}}{\text{Re}_{u,v} + \text{Re}_{i,j}} \right]^2 + \left[ \frac{\text{Im}_{u,v} - \text{Im}_{i,j}}{\text{Im}_{u,v} + \text{Im}_{i,j}} \right]^2 \quad (4.14)
\]

\[
\hat{W}_{x,y} = \begin{cases} W_{x,y} \cup d(u,v) & \text{if } |d(x,y)|^2 > \lambda \cdot \text{Corr}(u,v) < \delta \\ W_{x,y} & \text{else} \end{cases} \quad (4.15)
\]

iii) Select adapted values of $\delta$ and $\theta$, according to the noise level;

iv) Filter the wavelet coefficients according to (4.36);

\[
\hat{d}(i,j) = \begin{cases} d(i,j) \cdot (1 - \lambda / S) & \text{if } W > \theta \\ 0 & \text{else} \end{cases} \quad (4.16)
\]

v) Compute the inverse UWT of the filtered wavelet coefficients;

vi) Obtain the magnitude image from the absolute values of complex data.
4.4.1 Experimental Results

The performance of this method is evaluated by carrying out a qualitative and quantitative comparison. The robustness of the method is demonstrated with actual MRI data. The results provide both smoother looking images and those containing finer structures. In practice, the performance of a denoising method mainly lies on the preference of the medical experts and the significance of image features. On a number of reference MR images, the great improvement of our method was demonstrated. Figure 4.7 displays an example of the original noisy and its denoised images. It is apparent that the proposed method better preserves edges while the noise is dramatically reduced.

![Figure 4.7 Denoising of real noisy MR image Using Context Modeling Denoising](image-url)
Figure 4.8 (a) shows the original noiseless image of a human brain, which is sufficiently clean as an ideal model. In simulations, complex white Gaussian noise at different levels was added to this image. Figure 4.8 (b) illustrates the quantitative performance of the proposed method, compared with others.

This method is a new and effective wavelet domain noise filtration technique, which is robust to various noise levels. The denoising for complex MRI data is exploited in an undecimated frequency, which benefits in suppressing artifacts like Gibbs’ ringing at edges after filtration. The algorithm aims to have high efficiency in an outstretched neighborhood of the assumed model. The arbitrary shape of the adaptive windows determines the signal variance estimating, and that the local Wiener filtering is affected by two important factors $\delta$ and $\theta$ resting with context calculation by the real and imaginary channels of complex numbers. The results show that this new filtering technique can remove noise to a great extent, and achieve far superior visual appearance than those of other methods. It turns out that the advantage of restoring image details and important features in desired regions of interest may become a powerful post-processing tool in many MRI applications. Furthermore, it has lower computational demands.
4.5 CONCLUSION

In this chapter, a brief review of the theory of wavelet based image denoising methods and Thresholding techniques are presented. And also a few standard wavelet thresholding methods were reviewed, implemented and compared. In the Context Modeling Denoising technique, the denoising for complex MRI data is exploited in an undecimated frequency, which benefits in suppressing artifacts like Gibbs’ ringing at edges after filtration. This algorithm aims to have high efficiency in an outstretched neighborhood of the assumed model. The arbitrary shape of the adaptive windows determines the signal variance estimating, and that the local Wiener filtering is affected by two important factors $\delta$ and $\theta$ resting with context calculation by the real and imaginary channels of complex numbers. The results show that this new filtering technique can remove noise to a great extent, and achieve far superior visual appearance than those of other methods. It turns out that the advantage of restoring image details and important features in desired regions of interest may become a powerful post-processing tool in many MRI applications. Furthermore, it has lower computational demands. Unlike many traditional schemes that directly threshold the wavelet coefficients, the adaptive wavelet thresholding technique multiplies the adjacent wavelet subbands to amplify the significant features and then applies the thresholding to the multiscale products to better differentiate edge structures from noise. The distribution of the products was analyzed and an adaptive threshold was formulated to remove most of the noise. Experiments on the MRI images show that the proposed scheme not only achieves high MSR and CNR measurements but also preserves more edge features.