Improved Signal Processing Algorithm Based on Wavelet Transform

Xiang Li and Haiyan Yao
Departments of Electronic Information and Electrical Engineering, Anyang Institute of Technology, Anyang, China
Email: whz101033@163.com, lix3972@163.com

Abstract—Wavelet analysis is a rapidly developing emerging discipline, at present; it has been widely used in practice. Study wavelet's new theory, new method and new application have important theoretical significance and practical value. Based on the problem of poor performance of using traditional wavelet transformation algorithm in signal denoising, this paper puts forward a improved scheme based on tradeoff between soft and hard threshold, the scheme is established on the basis of traditional soft threshold, hard threshold, and the obtained estimated wavelet coefficients value of this scheme are between soft threshold and hard threshold methods, so call it the tradeoff between soft and hard threshold method. Implementation steps of the improved scheme based on soft and hard threshold tradeoff are, firstly establishing wavelet coefficient estimator of soft and hard threshold tradeoff method, and adding factor in threshold estimator, so as to adjust the size of the estimated wavelet coefficients. Simulation experiments show that the proposed soft, hard threshold tradeoff based signal threshold improved denoising method shows a strong effect of the practical signal denoising, the obtained reconstructed signal SNR has been tremendously improved than the traditional denoising method.

Index Terms— improved wavelet transform; Signal denoising; Signal processing; Threshold denoising

I. INTRODUCTION

As a new theory, wavelet analysis has indeed caused a great disturbance in science and technology. To mathematicians, wavelet analysis is a new branch of mathematics, it is the perfect crystal of functional analysis, Fourier analysis, spline analysis, harmonic analysis, and numerical analysis; in application fields, especially in signal processing, image processing, voice analysis and nonlinear science field, it is considered another efficient time-frequency analysis method after Fourier analysis. In principle, where there can be used Fourier analysis traditionally where we can take the place of wavelet analysis [1]. Wavelet analysis has good localization characteristics both in time domain and frequency domain, which overcome the disadvantages of traditional Fourier analysis [2], and because it uses the gradually fine time domain step to high frequency, thus it can focus any details of the analyzed signal, so the wavelet analysis has the laudatory title of "mathematical microscope" [3].

In recent years, wavelet theory has been further developed, people construct wavelet has many excellent properties at the same time, such as multiple function wavelet [4], M wavelet [5], etc., also to loosen the orthogonal wavelet conditions from another point of view, to study more general non orthogonal vectors, such as filter group, orthogonal wavelet translation, etc., making the wavelet theory more perfect. With the constant improvement of wavelet theory, its application field is becoming more and more widely.

Nowadays, the application field of wavelet analysis is very wide, it includes: many subjects in the field of mathematics; Signal analysis and image processing; Quantum mechanics, theoretical physics; Military electronic countermeasure and intelligent weapons; Computer classification and recognition; Artificial synthesis of music and language; Medical imaging and diagnostic; Seismic data processing; Large machinery fault diagnosis, etc; In mathematics, for example, it has been used in numerical analysis, structural fast numerical method, curve surface structure, differential equation solving, cybernetics, etc. In the field of signal analysis, it has been used in filtering, noise, compression, transmission, etc. In the field of image processing, it has been used in image compression, classification, identification and diagnosis, decontamination, etc. And in the field of medical imaging, it has been used in B ultrasonic reduction, computed tomography (CT), imaging time of nuclear magnetic resonance (NMR), improving resolution, etc.

(1) The application in signal and image compression is an important aspect of wavelet analysis. It is characterized by high compression ratio, fast compression speed, remaining invariance of the signal and image features, and anti-jamming during the delivering. There are many compression method based on wavelet analysis, in which the successful ones include wavelet packet with best base method, texture model method in wavelet domain, the wavelet zero tree compression, vector compression of wavelet transform, etc.

(2) The application of wavelet in signal analysis is also very extensive. It can be used in border processing and filtering, time-frequency analysis, signal-noise separation and extraction of weak signals, fractal index, the signal recognition and diagnosis and multi-scale edge detection, etc.
(3) The application in engineering technology includes computer vision, computer graphics, curve design, turbulence, remote cosmic research and biomedical research.

In recent years, wavelet theory has been further developed, people construct wavelet has many excellent properties at the same time, in 1994, Xu [6] proposed a spatial correlation based noise removal method, filtering based on the wavelet coefficients of signal and noise between neighboring scales correlation, although this method is not precise enough, but it's very direct and easy to implement. In the process of implementation of the algorithm, the estimation of noise energy is critical. Pan [7] elicited the theoretical calculation formula of noise energy threshold and gave an efficient method of estimating the signal noise variance, making spatial correlation based spatial adaptive wavelet threshold denoising algorithm, the estimation of noise energy is critical. Pan method is not precise enough, but it's very direct and easy to implement.

In a word, in recent years, there are a lot of literatures about wavelet de-noising, some of them have achieved many good results, based on the analysis of these results, this paper made a lot of improvements, proposed some new algorithms, and compared with the original method to illustrate the advantage of the improved algorithm.

II. WAVELET TRANSFORM ALGORITHM

A. Overview of Wavelet Transform Algorithm

Apparently, time signal is only a rule that a physical quantity size changes with time, it can only directly reflect pieces of information of this physical quantity, a lot of important information contained within it [16].

Signal processing is a fabrication of a certain signal [18]. For digital signal processing, the software is especially important, which is closely related to the mathematical method of signal analysis. Frequency domain method of digital signal processing is using discrete Fourier transform (DFT) to convert the discrete time signal sequence into the frequency domain, getting the signal spectrum. So it often called spectral analysis. Now spectrum signal processing has become one of the most basic and most sophisticated signals processing method. The reason include: first it’s because in 1965, J.W.C ooley and J.W.T ukey put forward the fast Fourier transform (FFT) algorithm, which reduces the Fourier transform time by several orders of magnitude, the transform time should be relatively wide, for the purpose of giving accurate high frequency information, the time interval should be relatively small, for the purpose of giving accurate high frequency information, the time interval should be relatively wide, for the purpose of giving a complete information of one cycle. Fourier transforms is useless on this point.

In order to overcome the shortage of Fourier exchange algorithm, it appears a kind of wavelet exchange algorithm.

As a analysis tool who can automatically adjust along with the change of frequency, Wavelet transform has been greatly developed since mid 1980s, and applied in areas of signal processing, computer vision, image processing, speech analysis and synthesis.

The emergence of wavelet analysis method can be traced back to 1910 years; Haar put forward the Haar standard orthogonal basis. And in 1938, Littlewood – Paley established the L-P theory to Fu cover series. In order to overcome the shortage of the traditional Fourier analysis, in the early eighty s, scientists have used the concept of "wavelet" for data processing, in which the famous is in 1984 when a French geophysicists Morlet adopted wavelet concept to store and express the seismic signal of petroleum exploration. Exploration in mathematics is mainly the “atom" and "elements" theory founded by R.C ofifman and G.W eiss, these "atom" and "molecular" constitutes the part of the base in different function space. L. C arleton used alike "wavelet" functions to construct the unconditional basis in space $H^1$ of Stein and Weiss. Until 1986, the French mathematician Meyer successfully constructed a smooth function $\psi$ with certain attenuation, the binary flexibility and translation {$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{j}t - k)$} constructed the standard orthogonal basis of $L^2(R)$.

Lemarie and Battle also put forward respectively the wavelet function with exponential decay after Meyer. In 1987, Mallat uses the concept of multi-resolution analysis, unifies the various specific wavelet constructions, and puts forward the current widely used Mallat fast wavelet decomposition and reconstruction algorithm. In 1988, Daubechies constructed the orthogonal wavelet basis with compactly support. Coifman, Meyer et al., in 1989 introduced the concept of wavelet packet. Spline function based single orthogonal small basis was put forward by Cui Juxing and Wang Jianzhong in 1990. In 1992, A.C ohen, I. D aubechies et al. constructed biorthogonal wavelet base with compactly support. The same period, the relation between wavelet transforms and filter group also got further research. The basic theory of wavelet analysis was basically established.
In recent years, a simple effective wavelet constructing method - Lifting Scheme get a great attention and development. Using lifting scheme can decompose all the existing compactly supported wavelet into basic steps, in addition, it also provides a powerful means for nonlinear wavelet construction, and therefore, using the lifting scheme to construct wavelet is considered to be the second generation wavelet. Wavelet theory and its application is still in development, and it will get more deeper research in multi-scale method, the nonlinear wavelet structure on the non-stationary set and, non-uniform, time-varying signal processing etc in the future.

B. Constant Wavelet Transform

∀f(t) ∈ L1(R), f(t)’s constant wavelet transform (sometime it is called integral wavelet transform), defined it as:

\[ WT_c(a,b) = \int_{-\infty}^{\infty} f(t) \psi \left( \frac{t-b}{a} \right) dt, a \neq 0 \]  
\[ (1) \]

Or use the inner product form:

\[ WT_c(a,b) = \langle f, \psi_{a,b} \rangle \]  
\[ (2) \]

In the formula:

\[ \psi_{a,b}(t) = a^{-1/2} \psi \left( \frac{t-b}{a} \right) \]  
\[ (3) \]

If making the inverse transformation exist, \( \psi(t) \) should satisfy the admissibility condition:

\[ C_\psi = \int_{-\infty}^{\infty} \left| \hat{\psi}(\omega) \right|^2 |\omega| d\omega < \infty \]  
\[ (4) \]

In the formula, \( \hat{\psi} \) is the Fourier transform of \( \psi(t) \).

Here, the inverse transformation is

\[ f(t) = C_\psi^{-1} \int_{-\infty}^{\infty} \psi_{a,b}(t)WT_c(a,b) db \frac{da}{a^2} \]  
\[ (5) \]

\( C_\psi \), this constant limits the class of function \( \psi \) belongs to \( L^2(R) \) which can serve as “basic wavelet (or mother wavelet), especially require \( \psi \) as a window function, then \( \psi \) should belongs to \( L^1(R) \), that is

\[ \int_{-\infty}^{\infty} |\psi(t)| dt < \infty \]  
\[ (6) \]

So \( \hat{\psi}(\omega) \) is a continuous function in \( R \). we can get from formula (4) that \( \psi \) must be zero at origin, that is

\[ \psi(0) = \int_{-\infty}^{\infty} \psi(t) dt = 0 \]  
\[ (7) \]

It can be found from formula (6) that the wavelet function has oscillatory.

The transform of constant wavelet has the following characters:

Property 1 (linear): assuming \( f(t) = \alpha g(t) + \beta h(t) \), then

\[ WT_c(a,b) = \alpha WT_c(a,b) + \beta WT_c(a,b) \]  
\[ (8) \]

Property 2 (translation invariance): if \( f(t) \Leftrightarrow WT_c(a,b) \), then \( f(t-\tau) \Leftrightarrow WT_c(a,b-\tau) \).

Translation invariance is a very good nature, in practice, although discrete wavelet transform used more widely, but in the case of needing translation invariance, discrete wavelet transform cannot be used directly.

Property 3 (flexible degeneration): if \( f(t) \Leftrightarrow WT_c(a,b) \), then

\[ f(\tau t) \Leftrightarrow \frac{1}{\sqrt{\tau}} WT_c(\frac{a}{\tau},\frac{b}{\tau}) \]  
\[ (9) \]

Nature 4 (redundancy): it exist redundancy of information expression in the continuous wavelet transform. Its performance is unique of the reconstruction formula of continuous wavelet transform to restore the original signal, the wavelet kernel function \( \psi_{a,b}(t) \) exist many possible choices. Despite the existence of redundancy can improve the signal stability of the calculation, but increase the difficulties of analysis and interpretation of wavelet transform results.

C. Discretization of Continuous Wavelet Transform

Because it exist redundancy in continuous wavelet transform, so it is necessary to clarify that for reconstructing signal, what kind of discretization should be taken for the variance \( a \), \( b \) to eliminate the redundancy in transform, in practice, usually taking \( b = \frac{k}{2^n}, a = \frac{1}{2^n}; j, k \in Z \), here

\[ \psi_{a,b}(t) = \psi_{1/2^n}(t) = 2^n/2 \psi(2^n t - k) \]  
\[ (9) \]

Nano : \( \psi_{j,k}(t) \).

Transformation form: \( WT_c \left( \frac{1}{2^n}, \frac{k}{2^n} \right) = \langle f, \psi_{j,k} \rangle \)

In order to reconstructing signal \( f(t) \), it requires \( \{\psi_{j,k}\}_{j,k} \) is the Riesz basis of \( L^2(R) \).

Definition 1: a function \( \psi \in L^2(R) \) called a function \( R \), if \( \{\psi_{j,k}\}_{j,k} \) is a Riesz basis in the following sense: \( \{\psi_{j,k}\}_{j,k} \)’s linear span is dense in \( L^2(R) \), and it exist positive constant \( A \) and \( B \), \( 0 < \lambda < \infty \), making

\[ A \| \{c_{j,k}\}_j \|_2^2 \lesssim \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} |c_{j,k}|^2 \lesssim B \| \{c_{j,k}\}_j \|_2^2 \]  
\[ (10) \]

For all the double infinite square sum sequences, \( \{c_{j,k}\} \) established, namely

\[ \| \{c_{j,k}\}_j \|_2^2 = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} |c_{j,k}|^2 < \infty \]  
\[ (11) \]

Assuming \( \psi \) is a function \( R \), then it exist a unique Riesz basis \( \{\psi_{j,k}\}_{j,k} \) of \( L^2(R) \), the sense is

\[ \langle \psi_{j,k}, \psi^{j,m} \rangle = \delta_{j,l} \delta_{k,m}, j, k, l, m \in Z \]  
\[ (11) \]
The above is antithesis with \( \{ \psi_{j,k} \} \), here each \( f(t) \in L^2 (R) \) has the only series expression like (7):

\[
f(t) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} \langle f, \psi_{j,k} \rangle \psi_{j,k}(t)
\]

Particularly, if \( \{ \psi_{j,k} \}_{j,k} \) constructs the orthonormal basis of \( L^2 (R) \), there has \( \psi_{j,k} = \psi_{j}^k \), reconstruction formula is:

\[
f(t) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} \langle f, \psi_{j,k} \rangle \psi_{j,k}(t)
\]

III. SIGNALS DENOISING BASED IMPROVED WAVELET TRANSFORM ALGORITHM

A. Estimate the Soft and Hard Threshold Method

Assuming there is the following observation signal

\[
f(t) = s(t) + n(t)
\]

where \( s(t) \) as the original signal, \( n(t) \) is the whiter Gaussian noise of variance \( \sigma^2 \), obey \( N(0, \sigma^2) \). It is difficult to extract all the signal \( s(t) \) directly from the observed signals \( f(t) \), we must use other transformation methods as a tool. In recent years, using theory of wavelet transform for signal denoising provides powerful tools and ways to overcome the limitation of using traditional method to process non-stationary signal.

For 1 dimensional signal \( f(t) \), firstly we carry out the discrete sampling, we got \( N \) point discrete signa \( f(n), n = 0, 1, ..., N-1 \), the wavelet transform is

\[
WT_j(j,k) = 2^{-j/2} \sum_{n=0}^{2^j-1} f(n) \psi(2^{-j} n - k)
\]

\( WT_j(j,k) \) is the wavelet coefficient, in practice use, it is complex by using formula (15) to calculate, and \( \psi(t) \) does not display the expression in general, so we should depend on double scale equation, so as to get the recursion implement method of wavelet transform

\[
SF(j+1,k) = SF(j,k) * h(j,k)
\]

\[
WT_j(j+1,k) = S R(j,k) * g(j,k)
\]

In which \( h \) and \( g \) is respectively the low and high-pass filter corresponding to scaling function \( \phi(x) \) and wavelet function \( \psi(x) \), \( SF(0,k) \) is for the original signal \( f(k) \), \( SF(j,k) \) is the scale coefficient, \( WT_j(j,k) \) is the wavelet coefficient. Accordingly, Wavelet Transform reconstruction formula is

\[
S R(j-1,k) = S R(j,k) * \hat{h}(j,k) WT_j(j,k) * \hat{g}(j,k)
\]

For convenience, Wavelet Transform coefficient \( WT_j(j,k) \) recorded as \( w_{j,k} \). After taking the discrete wavelet transform for observation signal \( f(k) = s(k) + n(k) \), it can be seen by wavelet transform’s linear nature, the wavelet coefficient \( w_{j,k} \) got by decomposition still composed by two parts, one part is the wavelet coefficient \( s_{s}(j,k) \) corresponding to \( s(k) \), marked as \( u_{j,k} \), another part is \( n(k) \)'s corresponding wavelet coefficient \( s_{n}(j,k) \) marked as \( v_{j,k} \).

The basic thought of wavelet threshold de-noising is

1. Firstly carry out wavelet transform to noising signal \( f(k) \), got a group of wavelet coefficient \( w_{j,k} \);

2. Through carrying out the threshold process on \( w_{j,k} \), got the estimated wavelet coefficient \( \hat{w}_{j,k} \), making \( || \hat{w}_{j,k} - u_{j,k} || \) possibly small;

3. Using \( \hat{w}_{j,k} \) to carry out the wavelet reconstruction, got the estimated signal \( \hat{f}(k) \), namely the information after de-noising.

This paper mainly discusses how to estimate wavelet coefficient.

After taking out several times of wavelet decomposing for \( f(k) \), due to the space asymmetry distribute signal \( s(k) \)'s corresponding wavelet coefficient \( w_{j,k} \) at varies scale have relatively the bigger value at some certain position, these points corresponding to the change position and important information of original signal \( s(k) \), and the other position, \( w_{j,k} \)'s value is small, for white noise \( n(k) \), its corresponding wavelet coefficient \( w_{j,k} \) distributed uniformity at each scale, and along with the increase of the scale, \( w_{j,k} \)'s size value decreases . therefore, the common de-noising method is to find a proper number \( \lambda \) as the threshold(limit), setting the wavelet coefficient \( w_{j,k} \) lower than \( \lambda \) (mainly caused by noise \( n(k) \)) as zero, while for the \( w_{j,k} \) higher than \( \lambda \) (mainly caused by \( s(k) \)), then reserve it or contract it, getting the estimated wavelet coefficient \( \hat{w}_{j,k} \), it can be seen that it is caused basically by signal \( s(k) \), then carry out reconstruction of \( \hat{w}_{j,k} \), then we can reconstruct the original signal. The wavelet coefficient estimating method is:

Taking \( \lambda = \sigma \sqrt{2 \log(N)} \), define

\[
\hat{w}_{j,k} = \begin{cases} w_{j,k}, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases}
\]

It is called the hard threshold estimating method ; the soft threshold estimating defined as

\[
\hat{w}_{j,k} = \begin{cases} \text{sign}(w_{j,k}) |w_{j,k}| - \lambda), & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases}
\]
Figure 1. Hard threshold

Figure 2. Soft threshold

Figure 3. Soft and hard threshold compromise law

Figure 1 is the hard threshold method, and Figure 2 is the soft threshold method. Although these two methods are widely applied in practice, which also gets a good result, but this method has some potential defects. Such as in the hard threshold method, \( \hat{w}_{j,k} \) is not continuous at \( \lambda \), it may cause some oscillation by using \( \hat{w}_{j,k} \) to reconstruct obtained signal; although the \( \hat{w}_{j,k} \) estimated by the soft threshold method has a good continuity, but when \( |w_{j,k}| \leq \lambda \), \( \hat{w}_{j,k} \) and \( w_{j,k} \) always in the constant deviation, which directly affects the approach degree of reconstructed signal and real signal.

B. Improvement scheme

In view of the existing defects of wavelet estimating, this paper designs a soft and hard compromise scheme, which overcomes the defects of soft and hard threshold.

Define 2:

\[
\hat{w}_{j,k} = \begin{cases} 
\text{sign}(w_{j,k})|w_{j,k}| - \alpha \lambda ) |w_{j,k}| \geq \lambda \\
0, & |w_{j,k}| < \lambda 
\end{cases} (0 \leq \alpha \leq 1) 
\]

We call the above formula as the soft and hard threshold compromise wavelet coefficient estimator. Particularly, when \( \alpha \) takes 0 and 1, the above formula becomes the estimated method of hard and soft threshold. For general \( 0 < \alpha < 1 \), this data \( \hat{w}_{j,k} \) estimated by this method is between soft and hard method in the size, so we call it the soft and hard threshold compromise method. The model is shown in Figure 3.

The idea of this method is quite simple, also easy to understand, but it is good in de-nosing. It can be fund by careful analysis, the \( \hat{w}_{j,k} \) estimated by simple soft threshold method, its absolute value will always small in \( \lambda \) than \( w_{j,k} \), so it needs to reduce the deviation: but if reduce this deviation into zero (to hard threshold) is not possible the best, because \( w_{j,k} \) is composed by \( u_{j,k} \) and \( v_{j,k} \), it may makes \( |w_{j,k}| > |u_{j,k}| \) due to the effect of \( v_{j,k} \) (for most \( w_{j,k} \)), and our purpose id to make \( \| \hat{w}_{j,k} - u_{j,k} \| \) minimum, thus order \( |\hat{w}_{j,k}| \)'s value between \( |w_{j,k}| - \lambda \) and \( |w_{j,k}| \), then the estimated wavelet coefficient \( \hat{w}_{j,k} \) become more close to \( u_{j,k} \).

Based on this thought, we add factor \( \alpha \) in the threshold estimator, adjust properly the size of \( \alpha \) between 0 and 1, we can get a better de-nosing effect. In the experiment, taking \( \alpha = 0.5 \).

IV. SIMULATION RESULT

We use the proposed improved method to carry out the de-noising test for a period of noise signals. For comparison, the article also compared with traditional wavelet transform algorithm. When carrying out Wavelet decomposition, the biggest decomposition scale \( j \) for 3, taking different threshold \( \lambda \) on every scale, namely \( \lambda_j = \sigma_j \sqrt{2 \log(N) / \log(j+1)} \), in which \( \sigma^2 \) is for the variance of noise, \( N \) is for the length of the discrete sampling signals, \( j \) is for the decomposition scale.

This article uses the proposed improved method to carry out de-noise for a noise signal of SNR is 8.226270, then compare the results, Tab 1 is the recovered SNR after vary de-nosing methods and compared with corresponding RMSE, it can be seen from table 1 that the soft and hard threshold compromise method is obviously better than simple soft threshold methods in de-nosing, so as to verify the effectiveness of this improved method.
Because the selection of $\lambda$ is quite random, and it may affect the performance of varies methods, therefore, the paper tried another group of threshold $\lambda_j$, and we got the result as Table II.

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Soft thresholding</th>
<th>Hard threshold method</th>
<th>Soft and hard threshold compromise law</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR</td>
<td>15.27</td>
<td>14.33</td>
<td>15.58</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.172</td>
<td>0.192</td>
<td>0.166</td>
</tr>
</tbody>
</table>

It can be seen from table 2, the soft and hard threshold compromise method shows a better de-noising effect than pure soft threshold denoising method.

It should be pointed out that the selection $\lambda_j$ is not the best, if properly selected $\lambda_j$, the method can better reflect its superiority. In addition, for different $\lambda_j$, the comparison results of above method have some differences, but according to the author’s large number of trials, generally speaking, pure soft threshold and hard threshold methods’ stability is poorer, the dependence of $\lambda_j$ is strong, and for a given $\lambda_j$, at least one effect is not very good in soft threshold and hard threshold method; for soft and hard threshold method, no matter how to choose $\lambda_j$, it is always better than a simple soft threshold and hard threshold method.

In addition, in order to illustrate the superiority of the soft and hard threshold compromise method, this article also takes a de-nosing test for a noise Heavisine signal, figure 5 for the primitive Heavisine signal, figure 6 is for the original signal fixed with gaussian white noise signal, figure 7 is the obtained reconstructed signal after taking the proposed soft and hard threshold method to de-noising.

Set another example, for a noise information whose SNR is 6.8098 in Matlab:

$$x = 30 \sin(t) + 25 \sin(2t) + \text{rand}(n)$$

Respectively using soft threshold, hard threshold, soft threshold tradeoff method, and the proposed improved methods to carry out the simulation experiment. The Wavelet base used in the simulation is the db3 wavelet and decomposition layer is for 3, the results as shown in table III.

<table>
<thead>
<tr>
<th>Threshold value denoising method</th>
<th>SNR</th>
<th>Mean square error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft threshold method</td>
<td>6.9721</td>
<td>0.82825</td>
</tr>
<tr>
<td>Hard threshold method</td>
<td>7.6533</td>
<td>0.42006</td>
</tr>
<tr>
<td>Soft and hard threshold compromise method $a=0.05$</td>
<td>7.6640</td>
<td>0.41555</td>
</tr>
<tr>
<td>Soft and hard threshold compromise method $a=0.10$</td>
<td>7.6684</td>
<td>0.41365</td>
</tr>
<tr>
<td>Soft and hard threshold compromise method $a=0.15$</td>
<td>7.6665</td>
<td>0.41438</td>
</tr>
<tr>
<td>Improvement method $a=2000,b=13$</td>
<td>7.7321</td>
<td>0.38824</td>
</tr>
<tr>
<td>Improvement method $a=4000,b=13$</td>
<td>7.7336</td>
<td>0.38765</td>
</tr>
<tr>
<td>Improvement method $a=6000,b=13$</td>
<td>7.7341</td>
<td>0.38744</td>
</tr>
<tr>
<td>Improvement method $a=8500,b=13$</td>
<td>7.7345</td>
<td>0.38732</td>
</tr>
</tbody>
</table>

It can be seen from figure 7, the improved threshold de-noising method proposed in this paper shows a good effect on the actual signal denoising, the obtained reconstructed signal SNR has a significantly improvement than the traditional denoising method.

VI. CONCLUSIONS

In recent years, with the continuous development of wavelet theory, there produced some new wavelets with composite performance index, they can have some excellent properties which traditional wavelet is unlikely to have, researching the structure, characteristics and
implementation of these new type of wavelet algorithm and analyzes the relationship between them with the orthogonal basis is a very meaningful work. Based on application state quo of traditional wavelet noise ring algorithm in signal processing, improves the estimation method of wavelet coefficient, puts forward a kind of soft and hard compromise wavelet coefficient estimation, so as to improve the performance of signal denoising. The experimental results show that the proposed improved threshold de-noising method shows a good effect to the actual signal denoising, the obtained reconstructed signal SNR has a significantly improvement than the traditional denoising method.

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Xiang Li received the B.S degree in school of Automation and Electrical Engineering of Tianjin Tianjin University of Technology and Education, China, in 2001 and achieved the M.S. degree in School of Electrical and Information Engineering at Jiangsu University, China, in 2008. He is currently Lecturer in College of Electronic Information and Electric Engineering at the Anyang Institute of Technology, China. His research interests are mainly in Signal Processing and cognitive radio.

Haiyan Yao received the B.S. degree in School of Information Engineering at Zhengzhou University, China, in 2004 and achieved the M.S. degree in School of Electronic and Optical Engineering at Nanjing University of Science and Technology, China, in 2012. She is currently Lecturer in College of Electronic Information and Electric Engineering at the Anyang Institute of Technology, China. Her research interests are mainly in signal processing and wireless communication.