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Study on Signal Denoising in Casting Ultrasonic Testing Based on Translation Invariant

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Abstract

Interference noising originating from the ultrasonic testing defect signal seriously influences the accuracy of the signal extraction and defect location. A method based on the translation invariant discrete wavelet transform (TIDWT) wavelet shrinkage was proposed for signal extraction according to the characteristics of the casting defect ultrasonic signal. Both simulated and actual steel defect signals were tested. The results were compared with those of the traditional wavelet shrinkage estimate algorithm. The experiments show that Pesudo-Gibbs phenomenon can be suppressed efficiently. RMSE between the original signal and estimated one can be minished, SNR of estimated signal can also be improved. It is proved by the experiment that this method can denoise more effectively; the signal quality and performance parameters obtained by TIDWT is improved obviously

Keywords: ultrasonic signal, shrinkage estimator, translation invariance, wavelet denoising

1 Introduction

The cast steel piece can not avoid defect because of the restriction of process technics. Therefore, improving the check rate of cast steel defect has significant meaning not only to the quality of coal machine but also to the other quality control of machine equipments. At present, the cast steel defect is mostly tested by ultrasonic. However, the testing signals have been accompanied with various interference noises such as: electronic noise, structure noise, and impulsive noise, because of the influence of instrument and testing environment. Extraction or identifying interested signal from the noise is the core technology of ultrasonic testing application. During ultrasound defect testing, ultrasonic signal is broad pulse signal which is modulated by probe center frequency. Therefore, it is a time-changed signal. So time-frequency method is more efficient[1].

The estimation of a signal embedded in noise requires taking advantage of any prior information about the signal and the noise. Until recently, signal processing estimation was mostly Bayesian and linear. Non-linear smoothing algorithms existed in statistics, but these procedures were often ad-hoc and complex. Two statisticians,Donoho and Johnstone[2] proved that a simple thresholding algorithm in an appropriate basis can be a nearly optimal non-linear estimate. When the signal is slice smooth function, wavelet estimators has optimality properties and has a much lower risk[2]. In this method the choice of threshold is a key question. Otherwise it can not be got expect effect. Therefore, optimizing threshold and improving the computational performance of threshold estimator are the main points of this area.

According to the characteristic of cast steel ultrasonic signal, this paper puts forward the translation invariant discrete wavelet transform(TIDWT) threshold decision algorithm to extract the cast steel defect.

2 Traditional wavelet threshold de-noising

2.1 different characteristics between noise and signal in wavelet decomposition

If $f(x)$ is bounded, and that over (b_1, b_2), $WTf_\xi(x,a)$ satisfies[2]

$$|WTf_\xi(x,a)| \le Ka^a \qquad (1)$$

Then $f(x)$ is uniformly Lipschitz a on (b_1, b_2), the constant K is depend on $\xi(x)$. We can choose $a = 2^j$,which implies that

$$|WTf_\xi(x,a)| \le K2^{ja} \qquad (2)$$

From formula (2), it can be seen that the amplitudes after wavelet transform increases with the increase of scale j for a singularity big than zero, the amplitudes decreases with the increase of scale j for a singularity less than zero. Namely, white noise has negative singularity. However, the coefficient of WT has positive singularity. The signal singularity and different character of noisy wavelet transform property are the main bases differentiated signal and noisy among wavelet transform area [3-4] .

2.2 wavelet threshold estimator

A ultrasonic echo-signal contaminated by noise can be expressed as:

$$X = f + W \qquad (3)$$

We consider samples of a function f that is corrupted by Gaussian White noise. X is measure signal. W denotes an additive noise function. $W = \sigma z_i$, z_i is a sequence of N (0, 1) random variables with σ >0. We are interested in denoising of samples d via the TIDWT.

2.2.1 threshold estimator

In a basis $B = \{g_m\}_{0 \le m \le n}$, a diagonal estimator of f from X=f+W can be written[2]

$$\hat{F} = \sum_{m=0}^{N-1} d_m(X_B[m]g_m) \qquad (4)$$

Where $X_B[m] = \langle X, g_m \rangle$ .We suppose that W is a Gauss white noise with noise of variance σ^2. When d_m is thresholding functions, the risk of this estimator is shown to be close to the lower bounds obtained with oracle estimator.

Hard Thresholding

The core of wavelet threshold de-noising is estimation of wavelet coefficients. A hard thresholding estimator is implemented with :

$$d_m(x) = \rho_\Gamma(x) = \begin{vmatrix} x & if\ |x| > T \\ 0 & if\ |x| \le T \end{vmatrix} \qquad (5)$$

where T is the threshold.

Soft Thresholding

Soft thresholding decreases by T the amplitude of all noisy coefficients. The soft-thresholding estimator is defined by

$$d_m(x) = \rho_\Gamma(x) = \begin{vmatrix} x - T & 当 x \geq T \\ x + T & 当 x \leq -T \\ 0 & 当 |x| \leq T \end{vmatrix} \qquad (6)$$

2.2.2 threshold computation

Threshold T that is selected must pass the biggest level of noise. It is proved that the biggest amplitudes of noise just has a higher probability which is lower than general threshold $\sigma\sqrt{2\log N}$ Where σ is noise variance of the noisy signal. Therefore, threshold $T = \sigma\sqrt{2\log N}$ is often selected. If signal length is identified, selecting threshold will be changed to estimate noise variance σ, If M_x is in the middle position of wavelets coefficient $\{\langle X, \Psi_{l,m}\rangle\}_{0\leq m<N/2}$ within the smallest scale of noisy signal function X, it will be proved that the estimate value of noisy is $\sigma \approx median(x)/0.6745$, where M_x is the middle value of wavelet coefficient according the seriation, instead of average value.

3 TIDWT threshold decision algorithm

During the process of denoising by using traditional threshold algorithm, it is found that there are often produced oscillation among the part of signal sharp change. This is because the orthonormal wavelets are function cluster obtained by basis wavelets after dilating and translating. By increasing the scale, orthonormal wavelets sets cannot nicely match the part structure character of the signal from the point of multiscale, the oscillation phenomena are created, where the oscillation amplitude is closely correlated by the singularity of the signal. Therefore, the position of the singularity among the whole signals can be changed by changing signal range sequence, so the singularity can be reduced or removed. TIDWT threshold decision algorithm overcomes the defects of translation variability and easily aliasing caused by traditional threshold method[5], and can obtain lesser mean-squared error(MSE) and higher signal-to-noise-ratio(SNR) during the cast steel ultrasonic defect testing.

3.1 TIDWT and its property

Using the wavelet coefficient $\psi_{j,k}$, the function $f \in L^2(R)$ can be expanded into a wavelet series by

$$f = \sum_{j,k} \langle \psi_{j,k}, f \rangle \psi_{j,k} \quad j,k \in Z \qquad (7)$$

In expand space of the scaling function $\{\varphi_{j,k}\}$ and wavelet function $\{\psi_{j,k}\}$, Projection of the function f is represented by[6]

$$f = P^{j_0} f + \sum_{j\geq j_0} Q^j f \qquad (8)$$

Orthonormal discrete wavelet transform (DWT) has translation variability, TIDWT is obtained by computing all the translation coefficients of orthonormal wavelet transform and then averaging these coefficients, which is translation invariant and non-orthogonal and contains redundant information[7]. The function f can be split into a projection $P_R^j[f]$ and projections $Q_R^j[f]$ onto the space $L^2(R)$ [8].

$$f = P^{j0}[f] + \sum_{j>j_0} Q^j[f] \qquad (9)$$

In terms of the autocorrelation functions of the scaling function Φ and wavelet function ψ, the redundant projections $P_R^j[f]$ and $Q_R^j[f]$ can be expressed by :

$$P_R^j[f](y) = 2^j \int_{-\infty}^{\infty} f(x)\varphi(2^j(x-y))dx \qquad (10)$$

$$Q_R^j[f](y) = 2^j \int_{-\infty}^{\infty} f(x)\psi(2^j(x-y))dx \qquad (11)$$

The projections $P_R^j[f]$ and $Q_R^j[f]$ are translation invariant, they are alse expressed by the formula

$$P_R^j[f(g+\delta)](y) = P_R^j[f](y+\delta) \qquad (12)$$

$$Q_R^j[f(g+\delta)](y) = Q_R^j[f](y+\delta) \qquad (13)$$

Hence, TIDWT is translation invariant. Redundant projection is approximation of the function f. A comparison to the result for the projections of the classical non-redundant WT shows that introduction of redundancy decreases the approximation order of function.

3.2 translation invariant wavelet threshold algorithm

TIDWT algorithm estimates all translations of f and averages them after a reverse translation. For all $0 \le p < N$. The estimator $\tilde{F}^p$ of f^p is computed by thresholding the translated data $X^p[n] = X[n-p]$

$$\tilde{F}^p = \sum_{m=0}^{N-1} \rho_\Gamma(X_B^P[m]) g_m \qquad (14)$$

Where $\rho_\Gamma(x)$ is a hard or soft thresholding function. The translation invariant estimator is obtained by shifting back and averaging these estimates :

$$\tilde{F}[n] = \frac{1}{N}\sum_{P}^{N-1} F^P[n+p] \qquad (15)$$

4 Results and analysis of the experiments

First, the experiments of signal de-noising or suppression by HTDWT, STDWT and TIDWT are performed for ultrasonic simulation signal and actual defect signal on the computer to contrast and analyze the de-noising effect. Then it is directly compared the signals and contrasted the signal-to-noise-ratio(SNR) and *mean-squared error* by using above methods to do the de-noising experiment adopting actual cast steel ultrasonic defect signal

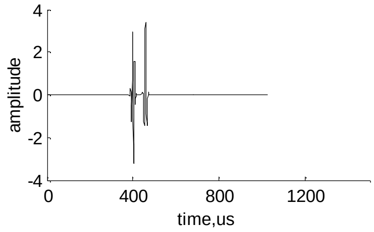
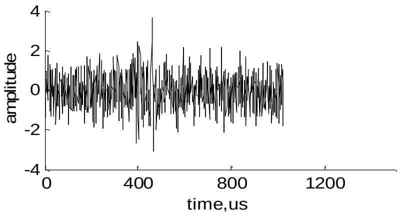
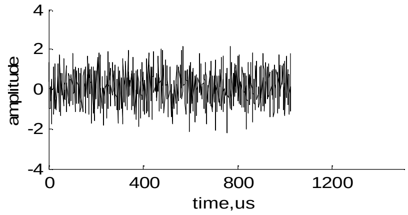


Fig.1 Original signal

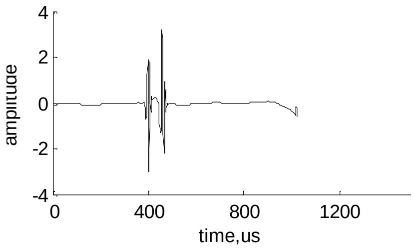
Fig.1 plots the simulation signal with two defects that their amplitudes and central frequencies are different, in which the sampling frequency of signal is 40MHz, Fig. 2(a1) gives the signal corrupted by random Gaussian White Noise, and is shown that the signal is almost entirely overwhelmed by noise. Figs. 2 (b1) (c1) (d1) show the de-noised ultrasonic simulation signals using HTDWT, STDWT and TIDWT respectively. Figs. 2 (b2) (c2) (d2) show error signal between the de-noised signal and the original signal. Simulation experiment result show that TIDWT is fit for ultrasonic signal de-noising, it can achieve better de-noising effect and improve SNR than HTDWT, STDWT method.



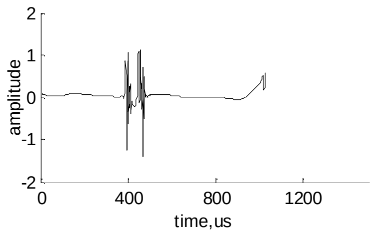
(a1)Noising signal



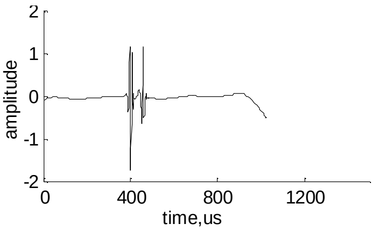
(a2) Error signal before de-noising



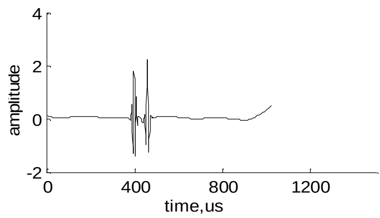
(b1) De-noised signal using HTDWT



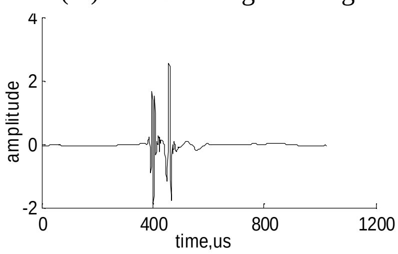
(b2) Error signal after de-noised using HTDWT

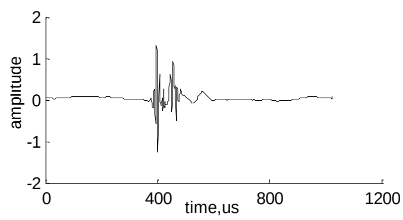


(c1) De-noised signal using STDWT



(c2) Error signal after de-noised using STDWT





(d1) De-noised signal using TIDWT (d2) Error signal after de-noised using STDWT TIDWT

Fig. 2 De-noising results for ultrasonic simulation signal

It is obtained that with the choice of 6-level decomposition, the SNR and RMSE has near-optimal value through de-noising experiments of wavelet scale decomposition for cast steel ultrasonic signal. Table 1 lists the SNR increment, RMSE of three methods. The SNR and RMSE are calculated by means of the expressions:

$$SNR = 10 \cdot \log \left[\frac{\sum_n f(n)^2}{\sum_n \left| \hat{f}(n) - f(n) \right|^2} \right] \tag{16}$$

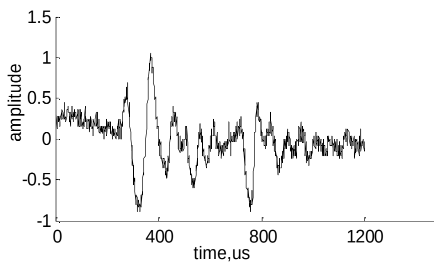
$$RMSE = \sqrt{\frac{1}{n} \sum_n \left[\hat{f}(n) - f(n) \right]^2} \tag{17}$$

where $f(t)$ denotes the original signal , $f(t)$ represents the de-noised signal.

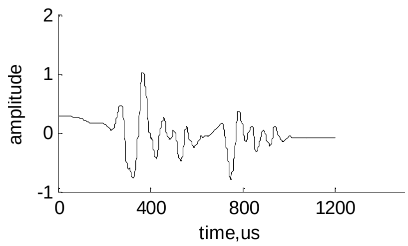
Tab.1 The de-noising performance of three methods

	HTDWT	STDWT	TIDWT
SNR/DB	5.5039	2.7594	7.8005
RMSE	0.1781	0.2442	0.0554

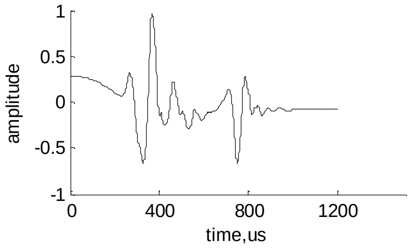
Fig.3(a) illustrates an actual defect signal, which has two $\phi 1$ mm traverse cylindrical cavities obtained by straight probe with the frequency of 10MHz, and its sampling frequency is 500MHz. Fig.3(b)-(d) show the de-noised signal resulting from HTDWT, STDWT and TIDWT respectively. By comparison, TIDWT is better than HTDWT and STDWT. It can separate two defect signals distinctly, and signal distortion is the lowest.

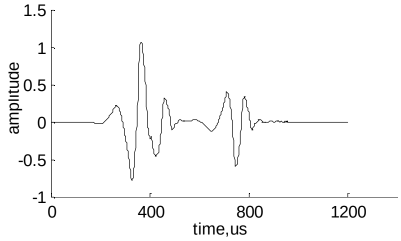


(a) Original signal



(b) De-noised signal using HTDWT





(c) De-noised signal using STDWT (d) De-noised signal using TIDWT

Fig. 3 De-noising results for actual ultrasonic defect signal

5 Conclusion

The de-noising experiment is show that TIDWT is superior to HTDWT STDWT from the de-noising effect. TIDWT is mainly suitable for the signal corrupted by random Gaussian White Noise and include some discontinuous dot. It can suppress Pesudo-Gibbs phenomenon efficiently. Experiment result proves that this method can more effectively de-noising and improve the signal quality and performance coefficients. But there still exist some questions that need to be more thorough research about ultrasonic signal extraction, such as, because of requesting real-time computation, The decrease computation complexity will be the next work.

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