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STUDY ON WAVELET DENOISING ALGORITHM BASED ON ACOUSTIC EMISSION LEAKAGE OF HEATERS

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ABSTRACT

This paper proposes an improved algorithm of wavelet threshold function in order to complement the inadequacy of the soft and hard threshold functions of traditional wavelet denoising algorithm. This proposed algorithm not only demonstrates good continuity and derivability, but also eliminates the constant error of soft threshold method, solving the problem of discontinuity of hard threshold function and the mutability of threshold function of non-negative dead zone so that the module value of wavelet transform decays exponentially, increasing the performance of wavelet denoising. The experiment shows that under a non-stationary and low SNR situation, the improved algorithm can effectively eliminates background noise, and is apparently superior to wavelet denoising algorithm that is based on traditional soft and hard threshold functions and the function of non-negative dead zone.

Keywords: Acoustic emission, Wavelet transform, Threshold denoising, Leakage.

1. INTRODUCTION

Generally, wavelet analysis is applied in the analysis of denoising algorithm of acoustic emission signals for detecting heater leakage, because the mutative scale of wavelet transform can let it focus on the details of signals and more effectively analyze mutative signals of acoustic emission. Thus, it has contributed to some achievements in the analysis of time-frequency, feature extraction, denoising and signal categorization of acoustic emission [1-5]. But the problem is that traditional wavelet denoising method lacks flexibility when it comes to practical detection, so that existing wavelet denoising methods are limited to laboratory analysis or postmortem analysis of acoustic emission data, and cannot be applied in online and real-time acoustic emission detection of heater leakage. To solve this problem, this paper intends to make improvements to wavelet threshold function and wavelet denoising algorithm based on the principles of wavelet denoising to achieve the optimal effect of denoising.

2. PRINCIPLES OF WAVELET DENOISING

The key technology of improving denoising effect of wavelet transform is to conduct denoising processing, whatever the wavelet coefficient. Wavelet transform denoising methods can be categorized into three main kinds according to their principles: wavelet extremum method, wavelet scale correlation method, wavelet threshold method. The above mentioned methods have the advantages of involving only a small amount of calculation, easy hardware connection, high speed, and effective denoising effect. At present, this method is widely applied in signal denoising based on acoustic emission leakage. The theories put forward by W.M. Chambers et al. can prove the above points. [6-8].

Acoustic emission signals can be divided into stationary signal and non-stationary signal. Non-stationary signal is also called the singularity of signals, which means the discontinuity of signals at a certain point or a certain derivative. Lipschitz exponent is usually used to express the non-stationary nature of signals [9]. The relationship between singularity of signals and the maximum value of the wavelet coefficient is established as follows:

$$\left| f(k_0+\tau)-f_n(k_0+\tau)\right| \le T\left|\tau\right|^{\delta} \quad n<\delta\le n+1 \tag{1}$$

In the inequality: δ - the Lipschitz exponent of the observed signal at, τ - a value that is sufficiently small, and n being both positive integers, n being the n th power polynomial of $f(k_0)$.

Assuming the module of wavelet transform coefficient of signal $f(k)$ is $\left|wf(a,b)\right|$, when $b_0\in(b_0-\tau,b_0+\tau)$ a positive integer is and the inequality $\left|wf(a,b)\right|\le\left|wf(a,b_0)\right|$ holds, then:

$wf(a,b_0)$ is the maximum denoising value of wavelet transform, and b_0 is the local maximum value point of wavelet transform of $f(k)$.

When the scale $a=2^j$, the singularity Lipschitz exponent δ of $f(k)$ and the wavelet maximum value $\left|w_{2^j} f(2^j,b_0)\right|$ match the following inequality.

$$\log_2\left|w_{2^j} f(2^j,b_0)\right|\le\log_2 A+\delta j \tag{2}$$

A represents relevant constant of the wavelet basis. It can be acquired through (3-2).

When the Lipschitz exponent of $f(k)$ $\delta < 0$, the maximum value of signal $f(k)$ $\left|w_{2^j} f(2^j, b_0)\right|$ will decrease as the scale of wavelet decomposition j increases; When the Lipschitz exponent of $f(k)$ $\delta > 0$, the maximum value of signal $f(k)$ $\left|w_{2^j} f(2^j, b_0)\right|$ will increase as the scale of wavelet decomposition j increases.

Hence: when the Lipschitz exponent $\delta > 0$, the maximum value of acoustic emission signal of leakage $wf(a, b_0)$ increases as the scale of wavelet decomposition j increases. When the Lipschitz exponent of the noise signal $\delta < 0$, the maximum value decreases as the scale of wavelet decomposition j increases.

Having established that, during wavelet transform, one can optimize the threshold value at different scales to change Lipschitz exponent δ , to improve the wavelet denoising effect, and to improve the detection of leakage signal. Put differently, if the maximum value point b_0 is less than the threshold value, it should be set as small as possible till zero. If not, it should be reserved. Eventually, the optimization of denoising effect can be realized through wavelet reconstruction.

3. IMPROVED WAVELET THRESHOLD DENOISING ALGORITHM

The leakage signals of high pressure pipes of power plants are non-stationary and one-dimensional signal [10]. According to the principles of wavelet denoising, the denoising model of one-dimensional signal is [01]:

$$f(k) = s(k) + \sigma \cdot n(k) \quad (3)$$

In the model, $f(k)$ is the observed signal that contains the noise signal, $s(k)$ is the true signal of leakage, $n(k)$ is the gaussian white noise signal, and σ is the noise intensity.

The acoustic emission of the observed signal leaked from the high pressure pipes of power plants $f(k)$ includes leakage signal and noise signal. According to the linear feature of wavelet transform, $f(k)$ passes the multi-scale wavelet decomposition. The wavelet transform coefficient $w_{j,k}$ acquired equals the transform coefficient of leakage signal $s(k)$ plus that of the noise signal $n(k)$. The transform coefficient $w_s(j,k)$ that $s(k)$ signal corresponds to is $u_{j,k}$, and that $n(k)$ signal corresponds to, $w_n(j,k)$ is $v_{j,k}$.

In this paper, wavelet transform is used to conduct multi-scale wavelet decomposition on noise signal. Subsequently, the wavelet threshold denoising method is applied in the denoising of coefficient of multi-scale wavelet decomposition. The optimal coefficient of wavelet decomposition of leakage signal is reserved, the coefficient of wavelet decomposition of noise signal reduced, which is followed by wavelet reconstruction based on the estimated wavelet coefficient $\widehat{w}_{j,k}$, and inverse transformation to improve acoustic emission signal of leakage and to reconstruct the observed estimation signal $\widehat{f}(k)$. The scheme of realizing the improved threshold denoising method is shown below.

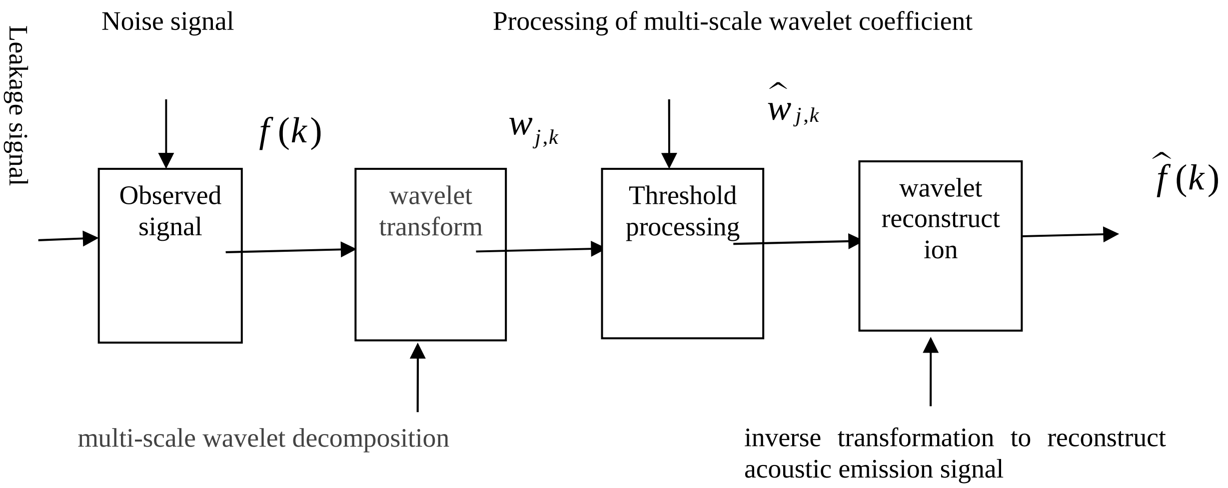


Figure 1. Scheme of realizing the improved threshold denoising method

4. IMPROVEMENT AND OPTIMIZATION OF WAVELET THRESHOLD FUNCTION

According to the principles of wavelet denoising, after wavelet transform, noise signals can be removed when the threshold processing is conducted again on the observed signal. Commonly used threshold processing functions include soft threshold function, hard threshold function [11] and some improved threshold processing functions [12].

Hard threshold function:

$$\tilde{w}_{j,k} = \begin{cases} w_{j,k} & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \tag{4}$$

Hard threshold function is a kind of threshold function that directly calculates and that reserves the wavelet coefficient which is more than the threshold value λ. Those that are less than λ will return to zero. The biggest advantage is that it reserves the peak features of the original signal. However, it is discontinuous, and is prone to vibration during wavelet reconstruction.

Soft threshold function:

$$\tilde{w}_{j,k} = \begin{cases} \operatorname{sgn}(w_{j,k})\left(|w_{j,k}| - \lambda\right) & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \tag{5}$$

Soft threshold function is continuous, and smoother during wavelet reconstruction. Normally in denoising, special preference is shown to soft threshold function, because better enhancement effect can be achieved. But there is a constant difference between the estimated wavelet coefficients. After threshold processing and the wavelet transform coefficient $w_{j,k}$ before the processing. The mutation information of the observed signal is easy to lose. During wavelet reconstruction, the SNR is low and the error of the mean square is large.

L. Breiman proposed the threshold function of non-negative dead zone [13-15] in compensation for the inadequacy of hard and soft threshold function. The function is:

$$\hat{w}_{j,k} = \begin{cases} w_{j,k} - \dfrac{\lambda^2}{w_{j,k}} & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \tag{6}$$

The threshold function of non-negative dead zone complements the inadequacy of soft and hard threshold functions and combines the advantages of both, so that denoising signals contain more details. In the meantime, it is smooth. The function ensures the continuity of the threshold value. As the scale increases, the wavelet coefficient of the leakage signal increases, and the wavelet coefficient of the noise signal decreases, realizing the increase of useful signal and the decrease of useless signal and better denoising effect. But there are still some inadequacies of the threshold function of non-negative dead zone. Namely, when improving the function, it is not considered that the decay of the upper bound of the module value of wavelet transform is exponential. Meantime, when $|w_{j,k}| < \lambda$, the threshold value of the function of non-negative dead zone returns to zero like that of soft and hard threshold functions, thus removing some useful signals, distorting some signals. In order to further optimize the design of the threshold value, this paper makes further improvements on the exponential function based on the threshold function of non-negative dead zone.

The improved threshold function is:

$$\hat{w}_{j,k} = \begin{cases} \operatorname{sgn}(w_{j,k})\left(|w_{j,k}| - \dfrac{\lambda^2}{2|w_{j,k}|} e^{2(\lambda - |w_{j,k}|)}\right) & |w_{j,k}| \geq \lambda \\ sgn(w_{j,k})\left(\dfrac{\lambda(e^{8|w_{j,k}|} - e^{8p}}{2(e^{8\lambda} - e^{8p})}\right) & |w_{j,k}| < \lambda \end{cases} \tag{7}$$

$p \in (0, \lambda)$, bring $w_{j,k} = -w_{j,k}$ into the function:

$$\hat{w}_{j,k} = -\hat{w}_{j,k} = \begin{cases} \operatorname{sgn}(-w_{j,k})\left(|-w_{j,k}| - \dfrac{\lambda^2}{2|-w_{j,k}|} e^{2(\lambda - |-w_{j,k}|)}\right) & |w_{j,k}| \geq \lambda \\ sgn(-w_{j,k})\left(\dfrac{\lambda(e^{8|-w_{j,k}|} - e^{8p}}{2(e^{8\lambda} - e^{8p})}\right) & |w_{j,k}| < \lambda \end{cases} \tag{8}$$

(1) It proves that $w_{j,k}$ demonstrates continuity at the threshold λ.

When $w_{j,k} \to \lambda^+$

$$\lim_{w_{j,k} \to \lambda^+} \hat{w}_{j,k} = \lim_{w_{j,k} \to \lambda^+} \operatorname{sgn}(w_{j,k})\left(|w_{j,k}| - \frac{\lambda^2}{2|w_{j,k}|} e^{2(\lambda - |w_{j,k}|)}\right) \tag{9}$$

$$\lim_{w_{j,k} \to \lambda^+} \hat{w}_{j,k} = \lambda - \frac{\lambda^2}{2\lambda} e^{2(\lambda - \lambda)} = \lambda - \frac{\lambda}{2} = \frac{\lambda}{2} \tag{10}$$

When $w_{j,k} \to \lambda^-$

$$\lim_{w_{j,k} \to \lambda^-} \hat{w}_{j,k} = \lim_{w_{j,k} \to \lambda^-} \operatorname{sgn}(-w_{j,k})\left(\frac{\lambda(e^{8|-w_{j,k}|} - e^{8p}}{2(e^{8\lambda} - e^{8p})}\right) = \frac{\lambda}{2} \tag{11}$$

From (10) (11) it is known that the improved threshold function is continuous at threshold λ.

(2) Proves the monotonicity of the threshold function

Here, this paper intends to acquire the derivative of (7) to prove its monotonicity.

Assuming $\hat{w}'_{j,k}$ is the first derivative of $\hat{w}_{j,k}$, then (3-29) can be turned into

$$\hat{w}'_{j,k} = \begin{cases} 1 + \dfrac{\lambda^2}{2w_{j,k}^2} e^{2(\lambda - w_{j,k})} + \dfrac{\lambda^2}{w_{j,k}} e^{2(\lambda - w_{j,k})} & |w_{j,k}| \geq \lambda \\ \dfrac{4\lambda e^{8w_{j,k}}}{e^{8\lambda} - e^{8p}} & |w_{j,k}| < \lambda \end{cases} \tag{12}$$

$e^{2(\lambda - w_{j,k})} > 0$, threshold $\lambda > 0$, so $\hat{w}'_{j,k} > 0$

Meantime, $e^{8w_{j,k}} > 0$, $0 < p < \lambda$, so $(e^{8\lambda} - e^{8p}) > 0$, $\hat{w}'_{j,k} > 0$

Through the above analysis, when $\hat{w}_{j,k} \geq 0$, $\hat{w}'_{j,k} \geq 0$, thus the function increases monotonically.

Fig. 2 compares various threshold functions when $\lambda = 1$.

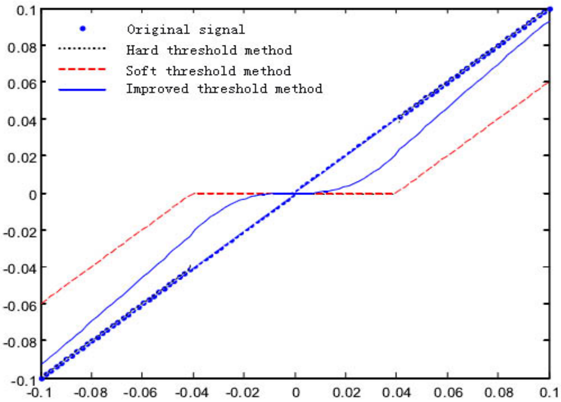
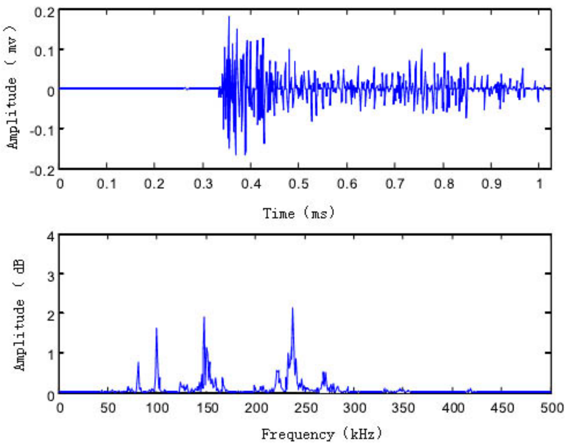


Figure 2. Illustration of the three threshold functions

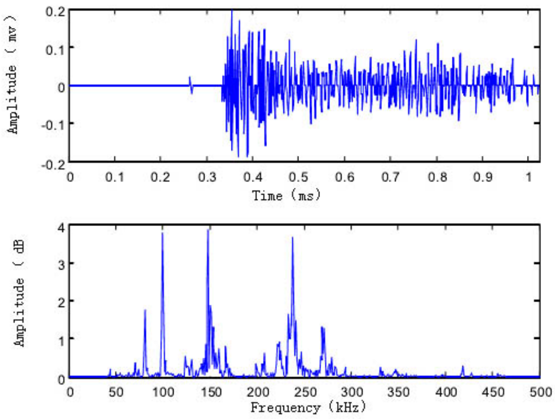
The Figure shows that the improved threshold function solves the problem of constant error of soft threshold method, and the discontinuity of hard threshold function. When $|w_{j,k}| = \lambda$, it makes improvements in terms of the mutability of threshold function. During reconstruction and addition of signals, there is no vibration like hard threshold function. When $|w_{j,k}| \geq \lambda$, threshold function is closer to hard threshold function, eliminating the constant difference between $\hat{w}_{j,k}$ and $w_{j,k}$, solving the problem of mutability of threshold function and complementing the inadequacy of threshold function of non-negative dead zone so that the module of wavelet transform decays exponentially, enhancing the performance of wavelet denoising.

5. EXPERIMENT AND ANALYSIS

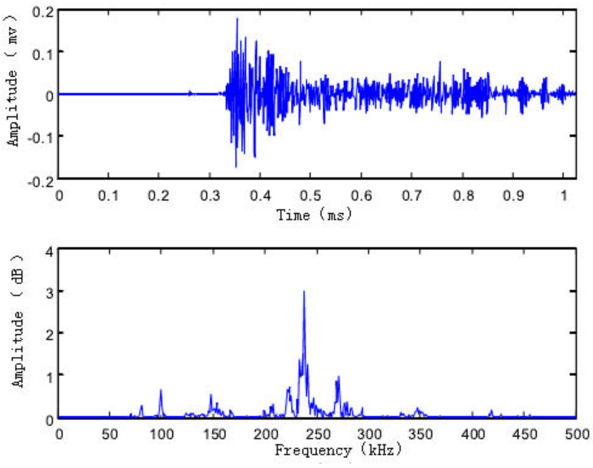
This experiment utilizes PCI-2 acoustic emission detection system produced by PAC company, US. The experiment is conducted on the leak test panel of heaters. Soft threshold function, hard threshold function and improved threshold function are used respectively to conduct denoising processing on the original signal, as is shown in the figure.



Denoising performance of soft threshold function



Denoising performance of hard threshold function



Denoising performance of the proposed method

Figure 3. Waveforms and frequency spectrums of various signals

This paper adopts the proposed wavelet threshold method, which can effectively reduce the influence of noise, restrain noise signal, and increase the SNR of leakage signal. Fig. 3 shows that the waveform features of denoising signals of the new improved function are more salient, which compensates for the inadequacies of soft and hard threshold functions, and can achieve better denoising effect.

6. CONCLUSIONS

This paper first introduces the principles of wavelet denoising based on the denoising algorithm for acoustic emission leakage of heaters, analyzes the inadequacies of existing wavelet threshold functions, and proposes an improved wavelet threshold denoising algorithm. On the other hand, to complement the wavelet denoising algorithm that is based on traditional soft and hard threshold functions and threshold function of non-negative dead zone, it proposes an improved wavelet threshold denoising algorithm. The improved threshold function solves the problems of mutability of hard threshold method and constant difference of soft threshold method. It also analyzes continuity and monotonicity, and proves the logic of improving the algorithm. Results show that under a non-stationary and low SNR situation, the improved algorithm can effectively eliminate background noise, and is saliently superior to traditional algorithm.

REFERENCES

1. Gyunyoung Heo, Song Kyu Lee, Internal Leakage Detection for Feedwater Haters in Power Plants Using Neural Networks [J], *Expert Systems with Applications*, Volume 39, Issue 5, April 2012, pp.5078-5086.
2. M. J. Eaton, R. Pullin, K. M. Holford, Acoustic Emission Source Location in Composite Materials Using Delta T Mapping [J], *Composites Part A: Applied Science and Manufacturing*, Volume 43, Issue 6, June 2012, pp.856-863.
3. Shao Hao, Jiang Shuguang, Wang Lanyun, Wu Zhengyan, King Factor of the Strata Overlying the Gob and a Three-Dimensional Numerical Simulation of the Air Leakage Flow Field [J], *Mining Science and Technology (China)*, Volume 21, Issue 2, March 2011, pp. 261-266.
4. Sandip Ghosh, Deb Mukhopadhyay, Samir Kumar Saha, an Experimental Analysis of Subcooled Leakage Flow Through Slits from High Pressure High Temperature Pipelines [J], *International Journal of Pressure Vessels and Piping*, Volume 88, Issues 8–9, August–September 2011, pp. 281-289.
5. D. Asher Ghertner, Matthias Fripp, Ding away Damage: Quantifying Environmental Leakage through Consumption-Based, Life-Cycle Analysis [J], *Ecological Economics*, Volume 63, Issues 2–3, 1 August 2007, pp. 563-577.
6. W. M. Chambers, N. J. McC. Mortensen, Toperative Leakage and Abscess Formation after Colorectal Surgery [J], *Best Practice & Research Clinical Gastroenterology*, Volume 18, Issue 5, October 2004, pp. 865-880.
7. Chang-Min Keum, Jin-Hyuk Bae, Min-Hoi Kim, Wonsuk Choi, Sin-Doo Lee, Ution-Processed Low Leakage Organic Field-Effect Transistors with Self-Pattern Registration Based on Patterned Dielectric Barrier [J], *Organic Electronics*, Volume 13, Issue 5, May 2012, pp. 778-783.
8. M. F. El-Amin, H. Kanayama, Boundary Layer Theory Approach to the Concentration Layer Adjacent to a Ceiling Wall at Impinging Region of a Hydrogen Leakage [J], *International Journal of Hydrogen Energy*, Volume 33, Issue 21, November 2008, pp.6393-6400.
9. X. Wu, S. Kaneko, Linear and Nonlinear Analyses of Sheet Flutter Induced by Leakage Flow [J], *Journal of Fluids and Structures*, Volume 20, Issue 7, October 2005, pp.927-948.
10. Chuanhu Ge, Guizeng Wang, Hao Ye, Analysis of the Smallest Detectable Leakage Flow Rate of Negative Pressure Wave-Based Leak Detection Systems for Liquid Pipelines [J], *Computers & Chemical Engineering*, Volume 32, Issue 8, 22 August 2008, pp.1669-1680.
11. K. Fujita, H. Morikazu, A. Shintani, *A Consideration on Pre- and Post-Instability of an Axisymmetric Elastic Beam Subjected to Axial Leakage Flow [J], .Journal of*

Fluids and Structures, Volume 23, Issue 3, April 2007, pp.463-478.

12. S. Abbasion, A. Rafsanjani, A. Farshidianfar, N. Irani, Rolling Element Bearings Multi-Fault Classification Based on the Wavelet Denoising and Support Vector Machine [J], *Mechanical Systems and Signal Processing*, Volume 21, Issue 7, October 2007, pp.2933-2945.
13. Zhou, Donghua H.; He, Xiao; Wang, Zidong; Liu, Guo-Ping; Ji, Yindong D., Leakage Fault Diagnosis for an Internet-Based Three-Tank System: An Experimental Study [C], *IEEE Transactions on Control Systems Technology*, June 13, 2011.
14. Ergün Tuncay and Yuzo Obara, Comparison of stresses Obtained from Acoustic Emission and Compact Conical-Ended Borehole Overcoring Techniques and an Evaluation of the Kaiser Effect Level [J], *Bulletin of Engineering Geology and the Environment*, 2012, Volume 71, Number 2, pp.367-377.
15. Qingli Dai, Kenny Ng, Jun Zhou, Eric L. Kreiger, Theresa M. Ahlborn, Damage Investigation of Single-Edge Notched Beam Tests with Normal Strength Concrete and Ultra-High Performance Concrete Specimens Using Acoustic Emission Techniques [J], *Construction and Building Materials*, Volume 31, June 2012, pp.231-242.