Research about Weak Signal Processing of Microstage Based on Wavelet Entropy

Cao Ruimin[a], Hao Lina[b*], Zhang Xinchao[c], Sun Hanyan[d]

School of Mechanical Engineering & Automation, Northeastern University, Shenyang, 110819, China.

[a]email: xiaojiacaoruimin@126.com, [b]email: haolina@me.neu.edu.cn(corresponding author),

[c]email: ZHANGXIN_CHAO@163.com ,[d]email: sunhanyan1031@sina.com

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Abstract. This paper deals with the research on conditioning and filtering scheme of weak signals for the micro-positioning-stage and its measurement & control system. Through the analysis of the general filtering scheme of the weak signals, and the combination with the performance index of the system, this paper filters the noises utilizing the weak signal adaptive threshold extraction method based on wavelet entropy. This paper carried out comparable simulation and experimental tests with the proposed threshold method. The test results show that the wavelet entropy based threshold extraction method can obtain higher SNR and SNRG.

Introduction

As one of the key technology for the development of modern scientific research and industrial technology, micro/nano positioning technology is widely applied in biomedical, precision instruments, microelectronics manufacturing, aerospace, super precision manufacturing, communication positioning, defense industry and other significant fields[1].

Signals in measurement & control system of microstage systems usually suffer the electromagnetic interference from the noise in the internal of system and random disturbance from the external environment. All of these types of noise can reduce the positioning accuracy of microstage system [2]. Since the signal-to-noise ratio (SNR) of the weak signal is less than 0 dB in most cases, absolute amplitude value of the measured useful signal is so small that it is easy to be drown in the noise.

Researchers made lots of contributions in the signal processing of microstages. SUN Hanyu et al. [3] proposed the forward linear prediction wavelet transform to de-noise the signal. Dong-sheng Yang et al. [4] developed the double coupled duffing oscillator to extract the weak signal for the position frequency; Jose L. San Emeterio et al. [5] used SURE threshold to cycle translation for wavelet de-noising. Peiming Shi et al. [6] adopted the stochastic resonance adjustment method to improve the multi-frequency weak signal in multi-scale noise. Dong Wang, et al. [7] utilized the joint sparse coefficient of wavelet approach to develop an extraction and adaptive noise reduction method, which is realized in multi-component signal to realize the bearing fault feature. Yujie MA [8] designed a weak signal acquisition system based on FPGA, in which, linear cumulative average algorithm is utilized on weak signal processing. This method can meet the high speed transmission and real-time processing, restrain noise, which improves the SNR of the target signal.

The wavelet threshold method has the features of simple algorithm and small computational complexity, thus it has been widely used in weak signal de-noising [9]. This paper aims at processing the signals collected from the microstage. Due to that the collected analog displacement signal of the microstage belongs to weak signals, amplitude precision is only in μV level, thus, the useful signals can easily be submerged in the noise. In addition, the system has requirements of real-time response. Therefore, it is necessary to design a kind of high-speed processing scheme for weak signal of microstage system.

Adaptive Threshold Extraction Algorithm Based on Wavelet Entropy

Adaptive threshold extraction method based on wavelet entropy introduces Shannon entropy theory into wavelet de-noising, which is used to represent the uniformity of signal probability distribution, reflecting the uncertainty and complexity of the signal. Due to the position of singularity in the original signal at different wavelet decomposition level is regular, while the singularity in noise is uniformly distributed and uncorrelated, therefore we can use the sparse degree of wavelet transform matrix to suppress independent components, and finally realize accurately positioning. When the wavelet basis function is a set of orthogonal basis, wavelet transformation has the feature of energy conservation. Through the orthogonal wavelet transformation of discrete signal x(n), the i^{th} scale of time *k* for high frequency coefficient becomes $d_{i,k}$, low frequency coefficient becomes $a_{i,k}$, the number of sampling point is *N*, and different resolution *i* equals to 0, 1,...The energy *M* can be expressed as following:

$$E_i = \sum_k |C_i(k)|^2 \quad (1)$$

Total energy of the signal E is:

$$\mathrm{E} = \sum_{\mathrm{i}} \sum_{\mathrm{k}} |\mathrm{C_i(k)}|^2 \quad (2)$$

The wavelet coefficients of each layer can be divided into t equal zones, then

$$\mathrm{E_{i,k}} = \sum_{\mathrm{k}}^{\mathrm{m/t}} |\mathrm{C_i(k)}|^2 \quad (3)$$

Among them, m is the number of sampling points. Total energy of i^{th} layer wavelet is:

$$\mathrm{E_i} = \sum_{\mathrm{k=1}}^{\mathrm{n}} \mathrm{E_{i,k}} \quad (4)$$

The probability of the k^{th} interval signal energy in the total energy on this scale is:

$$\mathrm{p_{i,k}} = \frac{\mathrm{E_{i,k}}}{\mathrm{E_i}} \quad (5)$$

Wavelet entropy in the k^{th} interval is:

$$\mathrm{S_k} = -\sum_{\mathrm{i}} \mathrm{p_{i,k}} \ln \mathrm{p_{i,k}} \quad (6)$$

Through calculating the wavelet entropy in each subinterval, and selecting the medium value of the subinterval whose entropy is largest as the variance of noise, we can implement adaptive threshold selection.

$$\mathrm{thre_i} = \sigma\sqrt{2\ln(\mathrm{N})/\ln(\mathrm{j}+1)} \quad (7)$$

High frequency coefficient components in each level need to threshold compression and quantization, among them, $\mathrm{thre_i}$ is the threshold of the high frequency wavelet coefficient in each level. *N* is the total number of sample points at different scales; σ is the estimated variance of noise,

$$\sigma = \mathrm{median}(|\mathrm{d_{1,max}}|)/0.6745 \quad (8)$$

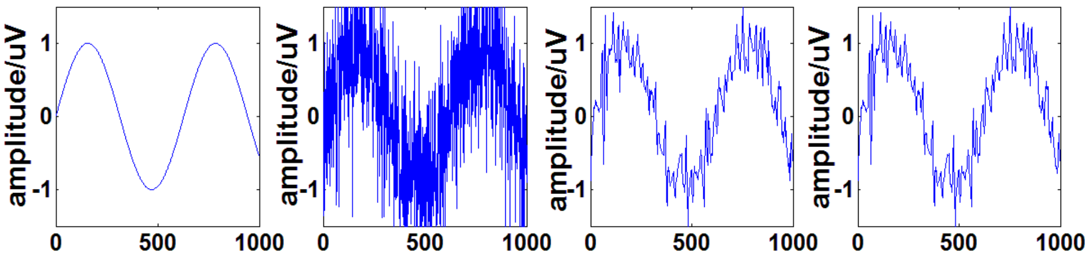
Among them, $median(|d_{1,max}|)$ stands for the wavelet coefficients medium value in the interval with largest wavelet entropy in the lowest layer sub band.

Finally, signals need to be reconstructed to get processed signals.

Simulation about Wavelet Entropy Extraction Algorithm

In the simulation, through adding Gaussian white noise in the original sine signal, the SNR of signal with noise can be adjusted. This paper utilized the method of adaptive threshold extraction of weak signal extraction based on the wavelet entropy to process the data, and made comparison with soft threshold de-noising method. Since the SNR of signals in this system is lower than 0 dB, 0.5 dB, -5 dB and -9 dB noise signal are selected to de-noise in this experiment.

(1) SNR=0.5 dB



(a) (b) (c) (d)

Fig.1 Results contrast of signal processing when SNR = 0.5 dB

(a) Original signal; (b) signal with noise; (c)soft threshold de-noise signal; (d)wavelet entropy de-noise signal

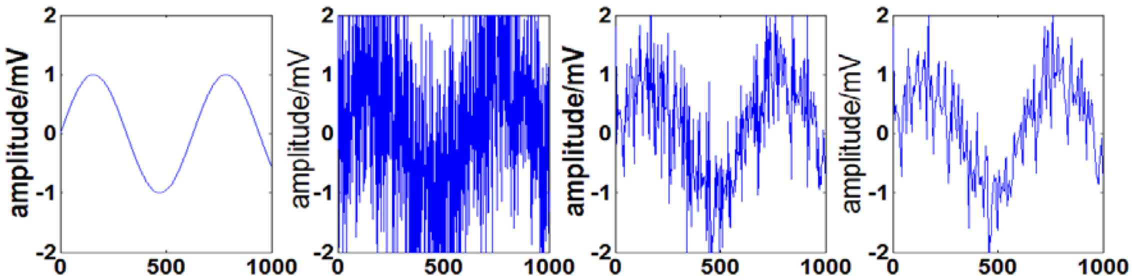
The filter effect of two methods is shown in figure 1. In this figure, the amplitude in the original signal is 1 mV. After adding white Gaussian noise, the original signal is polluted by noise, but the waveform is unchangeable roughly. Compared with two kinds of methods, we can know that when SNR = 0 dB, both signals are reconstructed well and the effect difference is not obvious, specific parameters are shown in table 1.

Table 1 Data contrast between soft-threshold method and wavelet entropy methods when SNR=0.5dB

De-noise method	Soft threshold de-noising	Wavelet entropy de-noising
SNR/dB	21.9170	22.1138
SNRG/dB	21.4170	21.6138
mean of residual ε/mV	2.2854e-04	2.2854e-04
mean square error σ/mV^2	0.3744	0.3649

(2) SNR=-5dB

The filter effect of two methods is shown in figure 2. After adding white Gaussian noise, the original signal are polluted seriously by noise, and waveform cannot be identified, both signals are still reconstructed well, but the de-noising effect based on wavelet entropy is better than de-noising effect based on soft threshold. specific parameters are shown in table 2.



(a) (b) (c) (d)

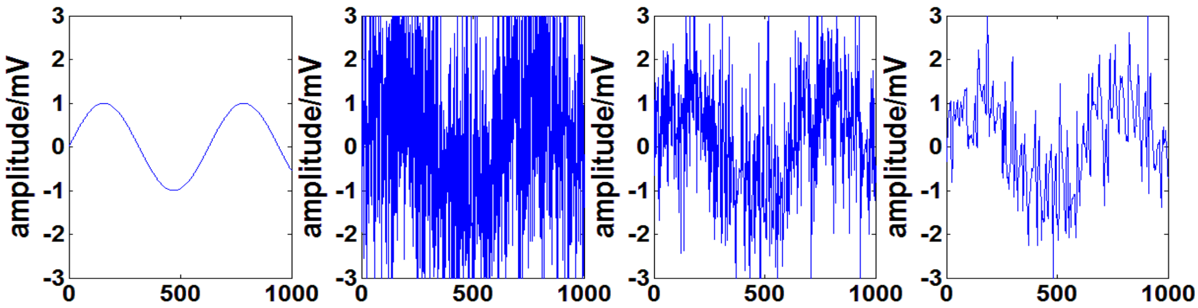
Fig.2 Results contrast of signal processing when SNR = -5 dB

(a) Original signal; (b) signal with noise; (c)soft threshold de-noise signal; (d)wavelet entropy de-noise signal

Table 2 Data contrast between soft-threshold method and wavelet entropy methods when SNR=-5dB

de-noise method	soft threshold de-noising	Wavelet entropy de-noising
SNR/dB	6.2013	10.4095
SNRG/dB	11.2013	15.4095
mean of residual errorsε/mV	4.2497e-04	4.2497e-04
mean square errorσ/mV^2	0.6865	0.5665

(3) SNR=-9dB



(a) (b) (c) (d)

Fig.3 Results contrast of signal processing when SNR = -9 dB

(a) Original signal; (b) signal with noise; (c)soft threshold de-noise signal; (d)wavelet entropy de-noise signal

The filter effect of two methods is shown in figure3. After adding white Gaussian noise, the original signal is polluted by noise, and the original signal waveform cannot be identified. Using wavelet de-noising, signals are reconstructed well, but signal processed by the soft threshold de-noising method has been unable to reconstruct well. Specific parameters are shown in table 3. Table 3 shows the comparisons with evaluation index between the two de-noising signal processing methods.

Through the simulation, we can acknowledge that utilizing adaptive threshold extraction method based on wavelet entropy in processing and filtering weak signals, no matter in high SNR or low SNR, the four parameters are superior to the soft threshold extraction, and the lower SNR, the more obvious advantage the wavelet entropy of adaptive threshold extraction methods perform.

Table 3 Data contrast between soft-threshold method and wavelet entropy methods when SNR=-9dB

de-noise method	soft threshold de-noising	Wavelet entropy de-noising
SNR/dB	*	0.2307
SNRG/dB	*	9.2307
mean of residual errorsε/mV	0.0011	0.0011
mean square errorσ/mV^2	1.0902	0.6912

Experimental Results Analysis

Devices used in this experiment are shown in figure 4. It mainly includes: HPV - 1 C 0300 A0300 PZT power supply, microstage, PZT SZBS 150/5×5/ 20,capacitance displacement sensors MA-0.5，24 V DC regulated power supply WP100-D-G, data acquisition card, PC and display.

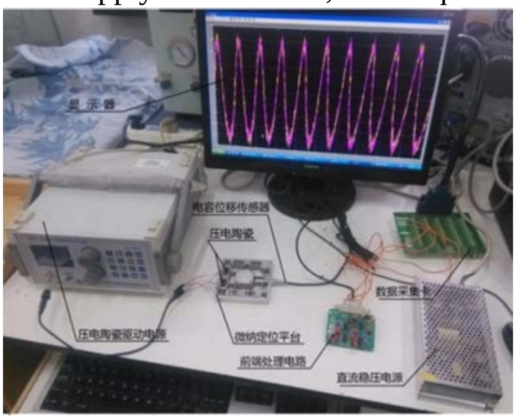
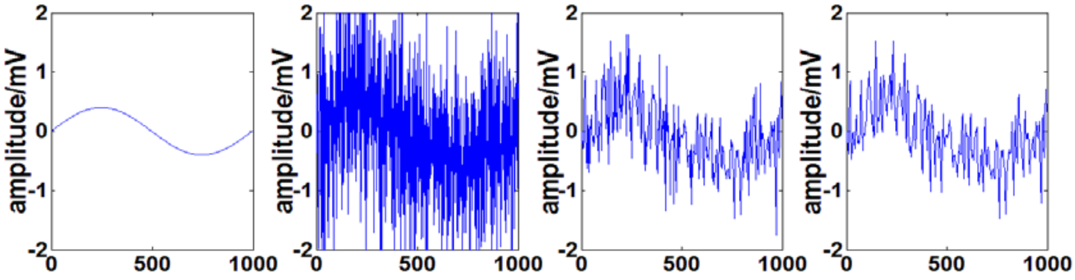


Fig.4 Experimental device of test system

Figure 5 is the waveform diagram for the experiment system. The original signal refers to the signal from waveform signal generator. Signal with noise refers to the signal waveform from signal acquisition card.



(a) (b) (c) (d)

Fig.5 Results contrast of measured signals processing

(a) Original signal; (b) signal with noise; (c)soft threshold de-noise signal; (d)wavelet entropy de-noise signal

Table 4 Data contrast between soft-threshold method and wavelet entropy methods to measured signals

de-noise method	soft threshold de-noising	Wavelet entropy de-noising
SNR/dB	-13.0402	5.0988
SNRG/dB	*	18.1390
mean of residual errorsε/mV	0.3601	0.0599
mean square errorσ/mV^2	0.3315	0.2355

By comparing the effect of two de-noising methods, we know that the effect of the wavelet entropy de-noising method is better than the soft threshold de-noising method. The specific parameters are shown in table 4. Table 4 shows the comparisons of the evaluation index of two de-noising signal processing methods.

Conclusion

Aiming at reducing the electromagnetic noise from the internal system and the random disturbance from the external environment, this paper deals with the research on conditioning and filtering scheme of weak signals for the microstage and its measurement & control system. Through the analysis of the filtering scheme of the common weak signals, and the combination of the performance index of the system, this paper proposes to filter the noises utilizing the weak signal adaptive threshold extraction method based on wavelet entropy, and to compare the simulation results and experimental results with the developed threshold method. The experimental results show that the threshold extraction method based on wavelet entropy can obtain higher SNR and SNRG.

In the future, researches will be focused on the study of the weak signal online processing. Combined with digital signal processing in the measurement and control system, we can get weak signals which are more similar to the real condition and it can verify the correctness of the scheme.

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