A Study on Vibration Recognition of Nano-imaging System Based on Wavelet Analysis

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Abstract: In order to intelligently diagnose the vibration types corresponding to various errors in nano-imaging process, firstly, all types of vibration signals were decomposed and reconstructed in nano-imaging process based on the wavelet transform. Thus, feature vectors of all types of vibration signals were extracted, so that the experimental personnel could take corresponding measures. Secondly, BP neural network model was established, and network training was carried out with the obtained feature vectors as the input information of network and all types of vibration sources as the output information of the network, which was finally passed through the actual inspection. The results showed that the feature value of all types of vibration signals extracted and obtained by wavelet feature, has merged together with BP neural network model, whose network recognition result are basically consistent with actual vibration signals. According to the results, it could effectively recognize all types of vibration signals during the nano-imaging process and has a higher practical guiding significance.

Keywords: Feature vector, Nano-imaging, Neural network, Vibration, Wavelet analysis, Signals.

1. INTRODUCTION

At the end of the 19th century, Ernst Abbe determined the resolution limit of optical microscope roughly to the half of visible wavelength, namely about 0.2 microns, which means that scientists could identify individual cells as well as some components of cells called organelles. But they failed to identify objects of smaller sizes with such a microscope. In 2014, however, we have succeeded in introducing the optical microscope into the size of molecular layer, and in the meanwhile, there has been a tremendous development in the molecular imaging technology.

Imaging technology of molecular layer could quantitatively monitor and detect the change of physiological and biochemical reaction in organism in real time [1], which has been successfully applied in the fields of medical care, biomedicine and therapeutic diagnosis research. Among them, molecular imaging technology could be divided into three major stages: firstly, molecular imaging technology could be applied in the test of some symptoms on tissue at the early beginning. After that, due to the generation and use of contrast agents, the initial molecular imaging technology had been improved to some extent, mainly manifested in the more accurate and rapid positioning of diseases formation point. However, because of the rapid expansion of nanotechnology and nano-imaging technology in recent years, both the imaging method and the molecular layer to be marked have been greatly improved, even which have achieved the difficulty layer of detection and marked single cells in the field of some diseases. Also, due to the rapid development of nanotechnology, today's medical imaging has the advantages of rapid diagnosis, minor side effects and strong pointedness and etc., so that the medical molecular imaging technology has great breakthrough. Nanotechnology not only could play an important role in the field of medical imaging, but also could detect and mark biological cells even in an extremely complicated environment.

However, as the nano-imaging object has reached the level of single cells and molecules [2], the entire process tend to be affected by a little environmental disturbance, such as the vibration of indoor central air-conditioner and so on, which would greatly affect the nano-imaging technology. So this paper focused on the analysis of interference factors in nano-imaging process. Through the single action of different sources of influence and recording their offset data and finally by extracting the signal features based on wavelet analysis [3-5]. The unique signal features of different sources of influence were analyzed. In the end, a pattern recognition system with different signals of influence and nanopositioning offset was established [6, 7] so as to take corresponding solutions when there is interference noise during nano-imaging process.

2. FEATURE EXTRACTION BASED ON WAVELET ANALYSIS

2.1. Basic Principles of Wavelet Transform

Wavelet analysis has outstanding ability of time-frequency analysis. Different from Fourier transform, wavelet transform could conduct multi-resolution conjoint analysis to data signals in time and frequency domains, so as to effectively extract information from the signals and realize the reasonable separation of signals in different frequency

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bands and times. These features of wavelet transform provide efficient and powerful tools for non-stationary description of dynamic signals, the separation of fault character frequency of components and parts of equipment, the extraction of weak information and the realization of early fault diagnosis. Among them, the basic wavelet functions are shown in formula (1):

$$\int_{-\infty}^{+\infty} \frac{|\phi(\omega)|}{\omega} d\omega < \infty, (\phi(t) \in L^2(R)) \quad (1)$$

In the analysis of actual signals, more objects of analysis were obtained by the extraction of discrete data, so that the one-dimensional binary discrete wavelet function obtained from the basic function transform of wavelets is shown in formula (2), and when the wavelet function $\phi_{jk}(t)$ constitutes an orthogonal wavelet decomposition of $L^2(R)$, there would be an orthogonal wavelet decomposition aimed at the discrete data $f(t) \in L^2(R)$, as shown in formula (3). In the formula, N is the decomposition layer of discrete data, d_k^j the detailed coefficient of decomposition feature of layer j, c_k^N the approximation coefficient of decomposition feature of layer N, and ϕ_{Nk} the orthonormal scaling function of discrete data.

$$\phi_{jk}(t) = 2^{j/2}\phi(2^j t - k), (j, k \in Z) \quad (2)$$

$$f(t) = \sum_{j=1}^{N}\sum_{k \in Z} d_k^j \phi_{jk}(t) + \sum_{k \in Z} c_k^N \phi_{Nk}(t) \quad (3)$$

$$EA = \sum_{k \in Z} | c_k^N |^2 \quad (4)$$

$$EB = \sum_{j=1}^{N}\sum_{k \in Z} | d_k^j |^2 \quad (5)$$

It could be deduced from the above wavelet functions that, the wavelet function $\phi_{jk}(t)$ of decomposition scale of the same discrete data was orthogonal to the scaling function ϕ_{Nk}, as shown in formula (6) according to Parseval's theorem. In the formula, EA is the detailed signal energy of layers 1 to N, EB the approximate signal energy of layer N. So the total energy of discrete digital signals in each layer is equivalent to one of primary discrete data. The energy information in each decomposition layer is part of feature information of primary signal. Therefore, it could directly dig out feature signals of primary discrete data by extracting the feature information of this part as the feature information or for the secondary compression and extraction.

$$\int_R | f(t) |^2 dt = \sum_{k \in Z} | c_k^N |^2 + \sum_{j=1}^{N}\sum_{k \in Z} | d_k^j |^2 \quad (6)$$

2.2. Experiment on Wavelet-Transform Analysis

From the perspective of spectrum analysis, wavelet transform is to decompose the signal into two parts, and in the decomposition of next layer, it could, once again, decompose the low-frequency part into lower frequency or higher frequency parts, and so on, and then to complete the wavelet decomposition of deeper layers. In this experiment, the selected wavelet basis functions were based on Matlab. The analysis based on separate vibration sources of nano imaging is shown in Fig. (**1**), and the wavelet basis function used was orthogonal wavelet basis function of “db5”, with 10 decomposing layers.

It could be seen from the results extracted by the above wavelet decompositions and reconstruction of signals of single vibration sources, layer 5 signals extracted by wavelet feature reflected the displacement characteristics of primary signals, among which periodic fluctuation presented when the displacement along the direction of x, y and z axes was in the lower sampling frequency, and it could also see from the primary signals that there was a larger fluctuation in this waveband, thus embodying that results extracted by the wavelet analysis have practical significance. Meanwhile, information extracted from layer 1 has the maximum correlation with primary data information, which has also the larger compression ratio, the larger the number of layers, the lower the correlation between extracted information and primary data information and the smaller the compression ratio. Compression ratio and related data of various layers of information extracted by wavelet are shown in Table **1**:

3. RECOGNIZE TYPES OF VIBRATION SIGNALS BY USING FEATURE VECTORS

It could be seen from the above the experimental result of wavelet analysis that, different layers of feature signals obtained by wavelet decomposition and reconstruction played a clearer role of extraction. Therefore, based on different vibration sources, this paper made a wavelet feature extraction, and then took the extracted feature signals as input vectors to establish a pattern recognition system for signals. The specific steps are as follows:

Step 1: wavelet decompose all types of signals of single vibration source collected, in which the wavelet basis function used in this paper is orthogonal wavelet basis function of “db5”, with 10 decomposing layers.

Step 2: reconstruct the decomposition coefficient obtained to get signal components corresponding to various layers, in which the reconstruct function used herein is also the orthogonal wavelet basis function of “db5”.

Step 3: resolve the mean value of each signal component obtained and form the final feature vector with mean value of each layer, of which there are 10 layers and each layer has three axial directions in total, including x, y, z axes, so the dimension of the feature vectors is 30.

Step 4: establish a pattern recognition neural network model, and take the above obtained feature vector as the input information and at the same time number all signals of single source as the input information of the model.

The extracted feature information of various vibration sources are shown in Table **2**:

When the established BP neural network and network training are convergent, the parameters are shown in

Table **3**, dynamic change of error during network training process is shown in Fig. (**2**).

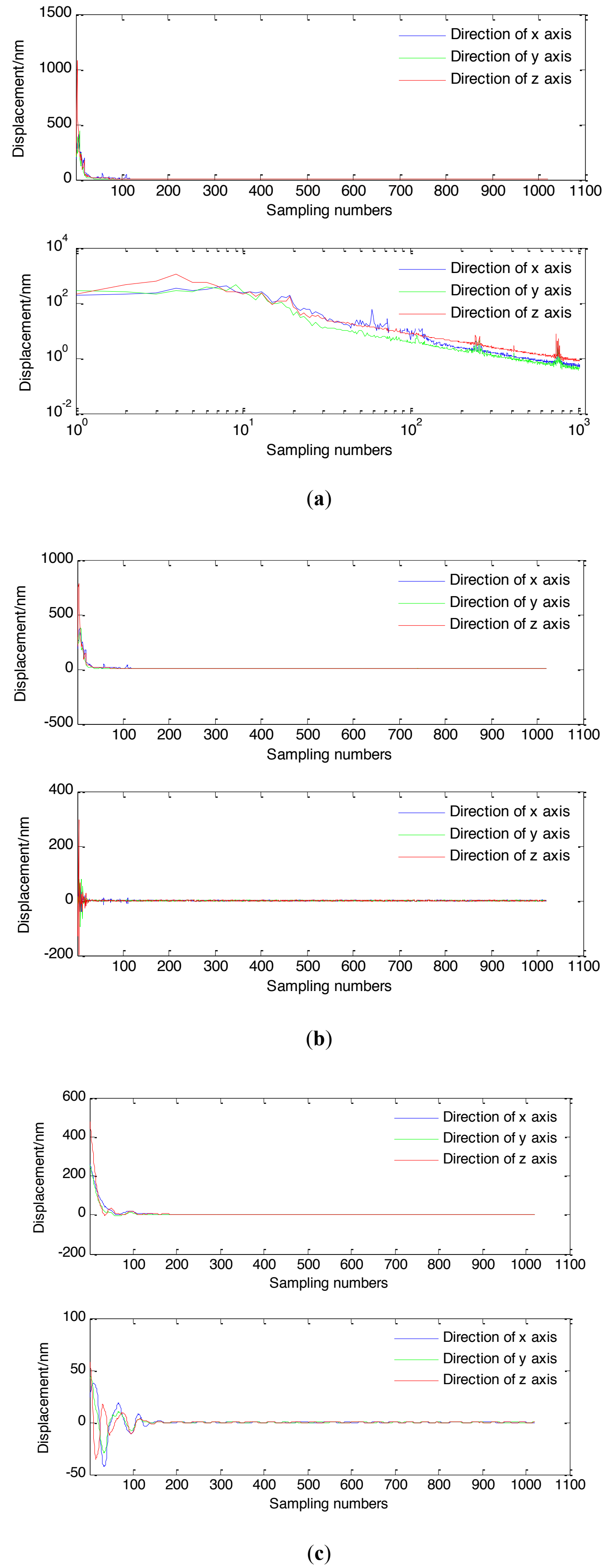

Fig. (1). Wavelet analysis of vibration data of experiment table; Fig. (**a**). is primary data; Fig. (**b**). shows extracted low and high-frequency signals of layer 1; Fig. (**c**). presents extracted low and high-frequency signals of layer 5

Table 1. Compression ratio and correlation result of each layer of signals extracted by wavelet of vibration sources of experimental table.

Extraction Layer	Compression Ratio	Displacement Correlation of x Axis	Displacement Correlation of y Axis	Displacement Correlation of z Axis
1	50.4416	0.9930	0.9850	0.9731
2	25.6133	0.9866	0.9753	0.9282
3	13.2483	0.9630	0.9623	0.9177
4	7.0658	0.9545	0.9461	0.9043
5	3.9254	0.9363	0.9355	0.8906
6	2.3553	0.9130	0.8939	0.8294
7	1.5702	0.8372	0.7843	0.7133
8	1.1776	0.7216	0.6332	0.5738
9	0.9814	0.5773	0.4840	0.4404
10	0.8832	0.4312	0.3534	0.3249

Table 2. Feature information values of each single vibration source (displacement/nm).

I	II	III	IV	V	VI
7.4738	7.8845	31.5526	5.9584	2.6382	13.7258
5.6992	9.9545	11.8599	4.1278	3.1156	12.1956
9.0500	7.2582	10.6891	6.0110	2.3378	13.2908
7.4662	7.8962	31.5530	5.9650	2.6338	13.5720
5.7211	9.8494	11.8762	4.1666	3.1316	12.0726
8.8911	7.2459	10.7138	6.0619	2.3516	13.2921
7.4198	7.8449	31.5367	5.9064	2.6868	13.6406
5.6672	10.0897	11.7915	4.0713	3.1026	12.2562
9.0513	7.2818	10.6088	5.9369	2.3349	13.1649
7.3750	7.7182	31.6063	5.8513	2.5553	13.3384
5.5421	9.5738	12.0619	4.0297	3.0495	11.7534
8.7739	7.0769	10.8960	5.7575	2.2916	12.8154
7.1088	7.4385	31.4553	5.5027	2.5304	13.1840
5.3118	9.5445	11.3595	3.7700	2.9252	11.7396
8.7143	6.8560	10.2906	5.3182	2.1688	12.0475
7.1557	7.6110	31.3901	5.2742	2.6911	14.0556
5.4751	10.3657	10.4859	3.6313	2.9880	12.8192
9.3240	7.1531	9.6439	5.0952	2.1457	12.1044
7.8968	8.6802	32.2733	5.2100	3.2789	16.7966
6.3791	12.9064	10.1392	3.7893	3.4533	16.0175
11.3146	8.5465	9.4519	5.3246	2.3557	13.6662
9.8211	11.2781	29.3907	5.4507	4.5201	22.9501
8.5967	18.3606	10.3510	4.2630	4.5516	22.9237
15.6908	11.7632	9.8642	6.1025	2.9388	17.8336
15.0854	18.1485	26.2033	6.5975	7.5303	38.6819
14.1827	31.6332	12.0071	5.7439	7.2963	39.8752
26.6074	19.7790	11.8790	8.4365	4.4436	28.7130
20.6149	25.1484	28.7342	8.0350	10.5164	54.2577
19.7363	44.5908	14.8963	7.4580	10.0672	56.3308
37.3093	27.7224	14.9570	11.0805	6.0184	39.7516

Table 3. Key parameters of network training and network convergence.

Network Training Parameters		Network Convergence Parameters	
Node number of 1st layer	6	Numbers of network training/ time	655
Node number of 2nd layer	6	Network training time/ s	10
Network target error	1.0*e-5	Network convergence error	$9.88*10^{-6}$
Network training function	traingd	Network fitting optimization	0.99999

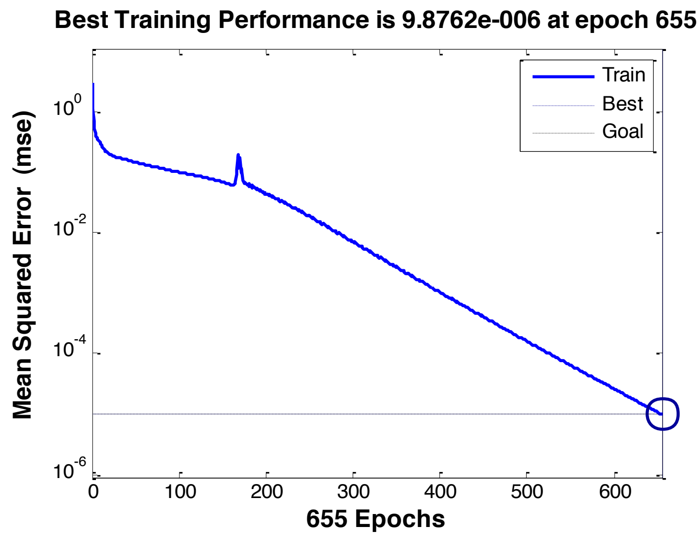

Fig. (2). Result of dynamic change of error during network training process.

Table 4. Network model output result.

I	II	III	IV	V	VI
1.0008	0.0008	0.0020	-0.0029	-0.0017	-0.0007
0.0027	1.0012	-0.0016	0.0012	0.0018	-0.0011
0.0008	0.0007	1.0008	-0.0010	-0.0005	-0.0007
0.0027	0.0010	-0.0007	1.0004	0.0014	-0.0014
-0.0006	0.0004	0.0027	-0.0044	0.9973	-0.0000
0.0012	0.0008	0.0005	-0.0005	0.0009	0.9992

The test results through the trained BP neural network model are shown in Table **4**, in which the results showed that: extract each type of single vibration signal based on wavelet and get its feature vector, meanwhile, establish BP neural network model with this feature vector. Through the test, recognition results were consistent with the types of actual vibration signals, which could effectively recognize all types of nano-imaging vibration signals, so that the experimental personnel could take the appropriate measures.

CONCLUSION

In this paper, all types of vibration signals were decomposed and reconstructed during the nano-imaging process based on wavelet transform, in which the orthogonal wavelet basis functions of “db5” were selected as wavelet basis functions of the decomposition and reconstruction to extract feature vectors of all types of vibration signals. After that, BP neural network model was established and network training was conducted with the obtained feature vectors as network input information and all types of vibration sources as network output information. Finally, untrained sample signals were used to detect and test. Results showed that, feature values of all types of vibration signals extracted by wavelet feature fused to BP neural network, model recognition results were basically consistent with all types of actual vibration signals, which could effectively recognize all types of vibration signals during nano-imaging process, so that the experimental personnel could take the appropriate measures.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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