Condition Diagnosis by Wavelet Transform and Neural Network for Rotational Machinery

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Abstract

It is important problem to diagnose the condition of rotational machinery. We generally pick up vibration of a shaft on such machinery by an accelerometer, and then we analyze the vibration by Fourier transform on conventional diagnostic technology. In this paper, to detect abnormal sign in vibrations we proposed a detecting method by discrete wavelet transform. We also construct an automatic diagnosis system by the detecting method and an neural network. We verified that our diagnosis system has high performance for some abnormal conditions through experiments of diagnosis.

1. Introduction

Industrial products such as mechanical parts are influenced by condition of manufacturing machinery. Therefore, it is very important that manufacturing machinery always keeps the best condition. Then we need a diagnostic technique with high performance[1]. Manufacturing machinery is rotational machinery in numerous cases. In conventional diagnostic technique we generally pick up vibration of a shaft on such machine by an accelerometer, and then we analyze the vibration by Fourier transform[2]. As against Fourier transform, wavelet transform can analyze vibration on time-frequency domain, and then it is suitable to detect non-stationary signal[3, 4]. One of purposes in our study is to develop detecting algorithm of abnormal signs from vibration signal by wavelet transform and an automatic diagnostic system utilizing neural networks.

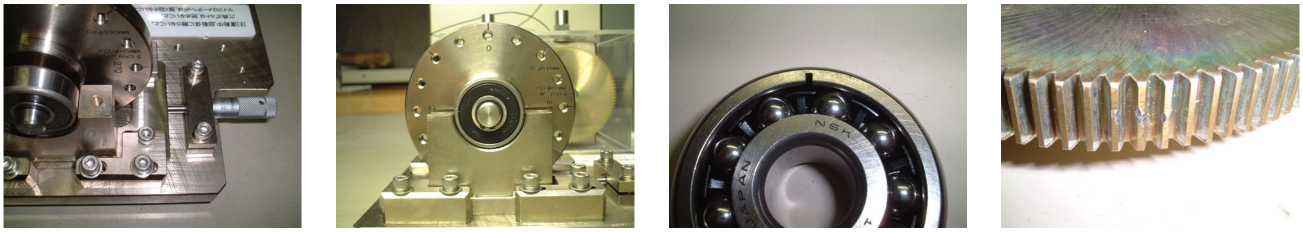
In this paper, to detect abnormal signs we propose a detecting method by discrete wavelet transform, DWT, auto correlation coefficients of DWT and envelope processing. We also construct an automatic, diagnostic system by the detecting algorithm and layerd neural networks. We investigate a performance of our diagnostic system through experiments of condition diagnosis.

2. Rotational machine

A rotational machine, RS–1100, made by ONO SOKKI is shown in Fig. 1. The machine consists of a motor at right region, coupled gears at center region, ball bearings and a holey flywheel with shafts at left region. We make the motor rotate at fixed speed in from 100 to 1740 rpm. We can adjust the shaft alignment by a micrometer. The adjustable slippage of shaft alignment is from 0 to 5mm with the step 0.01mm, see Fig. 2(a). We can also adjust a balance of the flywheel. The weight of holey flywheel is 650g, and has holes at intervals of 22.5 degree. By mounting bolts and nuts whose weight are about 1g into respective holes, we can make imbalanced condition of flywheel, see Fig. 2(b). A gear and a ball bearing are exchangeable for a chipped gear and a chipped bearing, which are shown in Figs. 2(c) and (d), respectively. Using the chipped parts and adjusters we intentionally make 4 abnormal conditions.

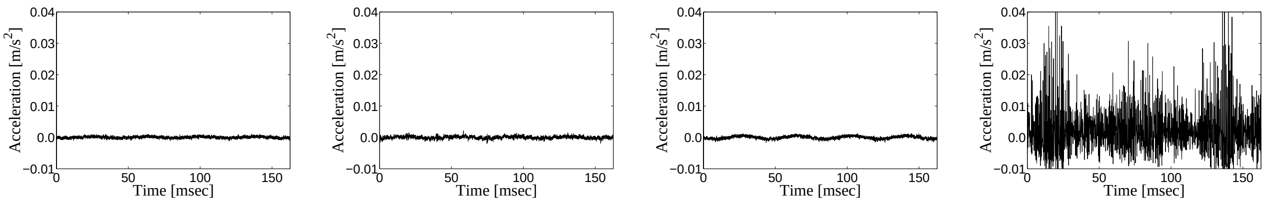
We acquire vibrations at two positions via an accelerometer, NP–3120, made by ONO SOKKI and a personal computer with the sampling frequency at 25kHz. Note that we measure vibration for bearing, out of shaft alignment and the flywheel at same point, but vibration of gear is measured at another point.

Figure 1: Experimental system of rotational machine.

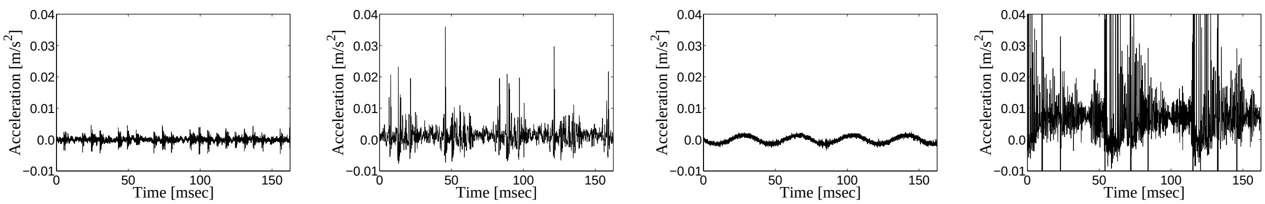


(a) Alignment adjuster (b) Holey flywheel (c) Chipped bearing (d) Chipped gear

Figure 2: Parts for making abnormal conditions.



(a) Normal condition (b) Out of alignment, 0.1mm (c) Imbalance flywheel, 0.2% (d) Normal gear



(e) Chipped bearing (f) Out of alignment, 0.5mm (g) Imbalance flywheel, 1.0% (h) Chipped gear

Figure 3: Vibration signals under normal or abnormal condition.

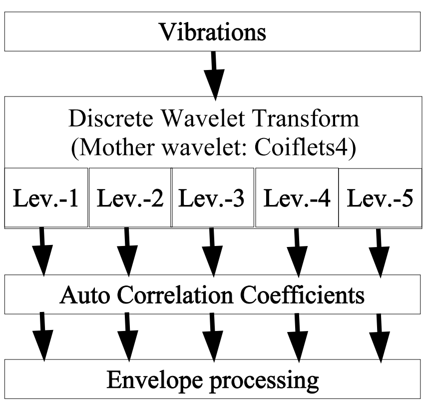


Figure 4: Process of detecting method for abnormal sign.

3. Detecting method of abnormal sign

We propose a method by DWT to detect abnormal sign in vibration signal. Proposed method consists of DWT, calculation of auto correlation coefficients and envelope processing, see Fig. 4. Where we selected Coiflets4 as mother wavelet from the viewpoint of reducing processing-time. We also fixed the analytic level of DWT to -5. Coefficients of DWT are not stationary for time, because DWT can analyze signal in time-frequency domain. Then calculating auto correlation coefficients, ACC, of DWT's coefficients, the ACC will be stationary. We finally implement envelope processing to acquire rough tendency of transition for an ACC.

4. Experimental Results

4.1. Detection of abnormal sign

We fixed rotative velocity of the motor at 1600rpm. Measured vibrations under normal and abnormal conditions are shown in Fig. 3. Where the percentage of imbalanced flywheel is calculated by dividing total weight of bolts and nuts by 650. Comparing the vibrations in Figs. 3(e), (f) and (g) from the vibration in Fig. 3(a), we can easily distinguish serious abnormal condition from the normal condition. However, slight abnormal conditions are indistinguishable from the normal condition, see Figs. 3(a), (b) and (c). It is also difficult to distinguish whether the gear is normal or abnormal from the vibration signal.

Let us analyze these vibrations by conventional method,

Table 1: Percentage of correct diagnosis on our system.

method		chipped bearing	out of shaft alignment			imbalanced flywheel					chipped gear
			0.1mm	0.3mm	0.5mm	0.2%	0.4%	0.6%	0.8%	1.0%	
DWT	Lev. -1	93	82	67	82	81	80	82	88	92	72
	Lev. -2	100	56	83	91	54	51	57	55	53	76
	Lev. -3	88	41	59	79	85	64	53	52	51	89
	Lev. -4	89	48	68	87	43	44	58	35	37	95
	Lev. -5	69	31	65	84	44	52	48	49	42	91
Fourier transform		96	66	79	93	65	61	70	78	91	100

i.e., Fourier transform. The power spectra are shown in Fig. 5. In Fig. 5(a) two spectra mainly appear around 27Hz and 4.8kHz, respectively. The spectrum of 27Hz denotes rotative velocity of motor, 1600rpm. Then the frequency of the other spectrum denotes eigenfrequency of the machine. Comparing respective power spectra in Fig. 5, we can easily distinguish the condition of gear. But slight abnormal conditions are still indistinguishable from the normal condition.

The signals in Fig. 6 are obtained through proposed method. You compare the respective figures. In the case of gear we can easily detect abnormal sign in level -4 or -5, see Fig. 6. We can also find abnormal signs for slight abnormal conditions, comparing Figs. 6(b), (c) and Fig. 6(a). We can detect abnormal sign of mechanical part by our method like this.

4.2. Automatic diagnosis by Neural Network

We constructed an automatic diagnostic system by 3-layerd neural networks. Where the number of neuron in input-layer, hidden-layer and output-layer are 4096, 10 and 1, respectively. We adopt the back-propagation method to make the neural network learn. We also adopt a neural network for diagnosis of a mechanical part. All coefficients of power spectra in one of Fig. 5 or all coefficients of each level in one of Fig. 6 are inputted to a neural network. The neural network is learned to completely diagnose whether the part is normal or abnormal. Then we will be able to diagnose the condition of each mechanical part from any vibrations.

A neural network is learned using each 10 vibrations in normal and abnormal conditions for a mechanical part. We evaluated the performance of a neural network for unknown each 50 vibrations of normal and abnormal conditions. The parcentages of correct diagnosis are shown in Table 1. The system by Fourier transform has percentages of correct diagnosis, more than 90%, for serious abnormal conditions, which are chipped bearing, chipped gear, out of shaft alignment(0.5mm) and imbalanced flywheel(1.0%). However the percentages are low, about 60%, for other slight abnormal conditions, which are out of shaft alignment(0.1mm) and imbalanced flywheel(0.2%). On the other hand, taking view of a certain level, proposed system can diagnose the condition of mechanical parts at equivalent performance of the method by Fourier transform for serious abnormal conditions. You also see that proposed system has high performance, that is, percentages of correct diagnosis, more than 80%, for slight abnormal conditions.

5. Conclusion

Utilizing discrete wavelet transform and neural networks, we proposed an automatic diagnostic system for a rotational machine. We also verified that our system has high performance against a conventional method by Fourier transform through experiments of diagnosis.

It is future work to develop diagnostic system with a more high performance and small amount of calculation than this system. Then the algorithm will be embedded in a one-chip microprocessor or a digital signal processor.

References

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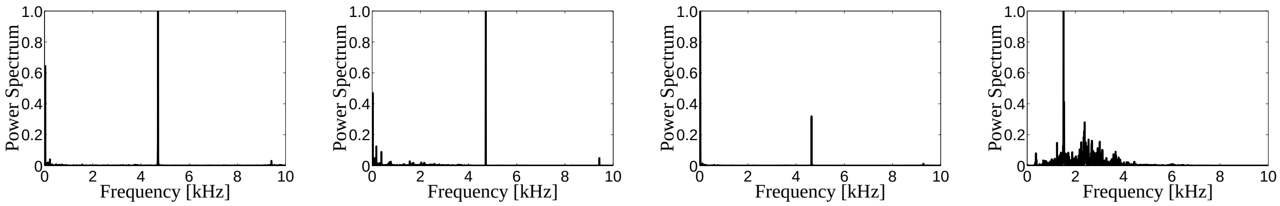
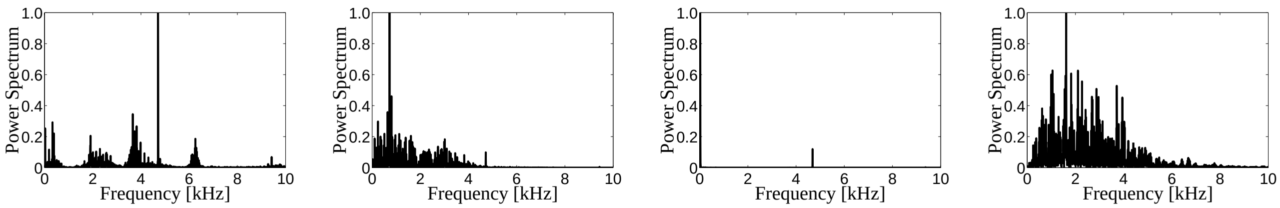
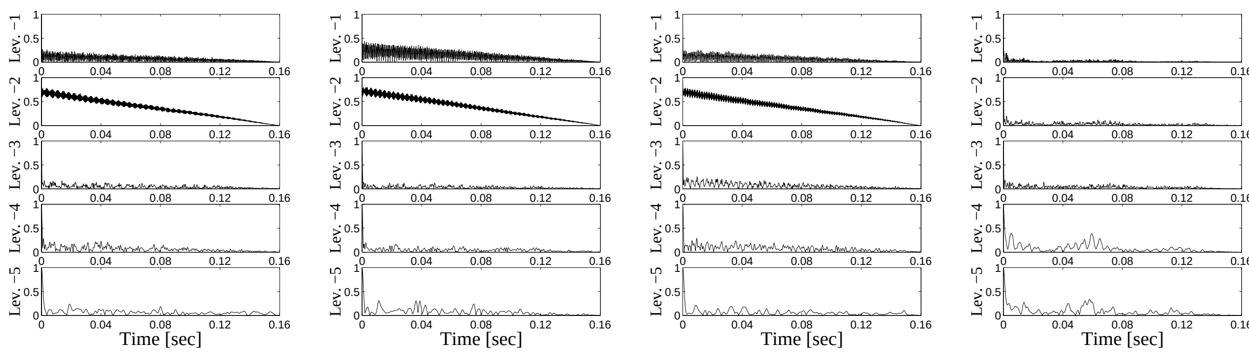


(a) Normal condition (b) Out of alignment, 0.1mm (c) Imbalance flywheel, 0.2% (d) Normal gear

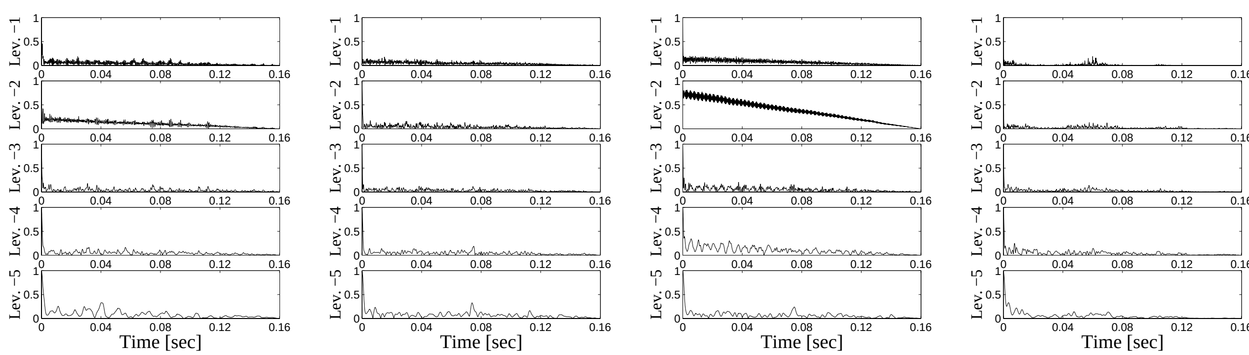


(e) Chipped bearing (f) Out of alignment, 0.5mm (g) Imbalance flywheel, 1.0% (h) Chipped gear

Figure 5: Power spectra of vibrations by Fourier transform.



(a) Normal condition (b) Out of alignment, 0.1mm (c) Imbalance flywheel, 0.2% (d) Normal gear



(e) Chipped bearing (f) Out of alignment, 0.5mm (g) Imbalance flywheel, 1.0% (h) Chipped gear

Figure 6: Coefficients on each level after proposed processing.