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Diagnosis of Rotating Machines By Utilizing a Back Propagation Neural Net

ByungGeun Hyun, Yoo Lee, and KwangHee Nam
Department of Electrical Engineering
POSTECH, Hyosa San-31, Pohang 790-784, Republic of Korea
Fax: 82-562-5699, kwnam@vision.postech.ac.kr.

Abstract-There are great needs for checking machine operation status precisely in the iron and steel plants. Rotating machines such as pumps, compressors, and motors are the most important objects in the plant maintenance. In this paper back-propagation neural network is utilized in diagnosing rotating machines. Like the finger print or the voice print of human, the abnormal vibrations due to axis misalignment, shaft bending, rotor unbalance, bolt loosening, and faults in gear and bearing have their own spectra. Like the pattern recognition technique, characteristic feature vectors are obtained from the power spectra of vibration signals. Then we apply the characteristic feature vectors to a back propagation neural net for the weight training and pattern recognition.

I. Introduction

Considerable attention has been devoted in recent years to the problem of fault detection and diagnosis in plants. In iron and steel plants, there are many machines in tandem, thus a failure in some of them will cause a serious trouble. There are great needs for checking machine operation status precisely in the iron and steel plants, because the equipments are very expensive and under harsh environments such as severe shocks, vibration, heat, friction, dusts, etc. Furthermore, due to the nature of steel mill, the possible damage made by stopping the process will make uncountable loss of money and time. Rotating machines such as pumps, compressors, and motors are the most important objects in the plant maintenance.

From the viewpoint of preventive maintenance, a regular check-up of equipment components by dismantling them when the process is shut down, is one method that assists an accurate diagnosis. But between regular check-ups, or if the process cannot be stopped, on-line quantitative diagnosis of the operating process is desirable.

In this experiment, we utilize a back-propagation neural network in the on-line diagnosis of rotating machine. Figure 1 is a block diagram of the diagnosis system. Like the finger print or the voice print of human, the vibration caused by any fault in some parts of a machine carries its characteristic feature. Specifically, the abnormal vibrations due to axis misalignment, shaft bending, rotor unbalance, bolt loosening, and faults in gear and bearing, have their own spectrum. We utilize the power spectrum in extracting characteristic feature vectors from the abnormal vibration like the pattern recognition technique. That is, the power spectrum of an abnormal vibration caused by each fault source is coded as its characteristic feature vector. Then, feature vectors are used in the neural net's weight training and recognition. We also test the performance of the trained neural net in recognizing the causes of vibrations. For this experiment, we made a vibration test bench in such a way that artificial faults could be made easily.

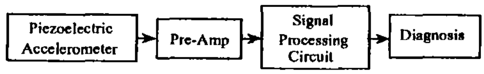

Figure 1: Diagnosis system block diagram

II. Vibrations in Rotating Equipment

Vibrations occur in elastic systems that generally consist of one or more masses connected to each other or to a fixed member by springs. A vibration is the motion of a body or system that is repeated after a given interval of time known as the period. The number of cycles of motion per unit of time is called the frequency.

Vibration monitoring is based on the principle that all systems produce vibration. The usual effect of excess vibration is premature wear of components such as bearings, gears, and couplings. Rather than attack the impossible problem of eliminating vibration, we propose to show how the proper interpretation of vibration data can be used to monitor the condition of operating mechanical equipment and lead to reductions in downtime and maintenance costs. When a machine is operating properly, vibration level is low and constant. However, when faults develop in the machine, the vibratory responses reflect them and their spectra also are changed. In many machines, vibration spectrum has a characteristic shape when the machine is operating properly, and it has other characteristic features for different faults. Diagnosis can be effectively performed by careful examination of the features associated with particular faults and their identification.

We can classify the sources of machine failures according to frequency range of their vibration. In the low frequency range ($0 \sim 5f_r$, f_r : rotating frequency of a machine), rotor unbalance, axis misalignment, axis bending, loose bolts are the major sources of abnormal vibration. In the mid frequency range($5f_r \sim$ 1kHz), abnormalities of gears are detected. And in the high frequency range(above 1kHz), the abnormalities of bearings are detected. These are shown in Table 1.

Unbalance is the most frequent faults in a rotating machine. Rotor unbalance is characterized by vibration at the running frequency f_r and vibration occurs in the radial direction. Vibration due to misalignment is characterized by a peak at two times the running speed of the component. If there is a loosening of a mounting bolt of a rotating machine with frequency, f_r, the harmonics—$2f_r, 3f_r$— are generated along with the subharmonics— $1/2f_r, 1/3f_r$— in its power spectrum of the vibration.

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Frequency Range	Faults	Running Frequency(f_r)	Vibration Direction
Low	Rotor unbalance	f_0	radial
	Axis misalignment	$2f_0,\ 3f_0$	axial
	Shaft bending	$2f_0,\ 3f_0$	axial
	Bolt loosening	$1/3f_0,\ 1/2f_0,\ f_0,\ 2f_0$	radial
	Oil whip	$(0.4 \sim 0.45)f_0$	radial
Middle	Gear faults	$5f_r \sim$1kHz	radial or thrust
High	Bearing faults	1kHz $\sim$	radial or thrust

Table 1: fault types and running frequency

The fundamental frequency component in the vibration of gears is the mesh frequency of the teeth of the gear. f_m can be calculated by the following equation,

$$f_m = Z_1 \times \frac{N_1}{60} = Z_2 \times \frac{N_2}{60}\text{Hz} \qquad (1)$$

where, Z_1, Z_2 are the number of teeth of each gear and N_1, N_2 represent rotational frequency of each gear in r.p.m. If there are faults in gear such as crack, frequency components $f_m \pm nf_r$ and $2f_m, 3f_m, \cdots$, grow larger and larger besides the mesh frequency f_m.

Faults in the bearing can be classified into three categories, i.e. , inner race defects, outer race defects, and ball defects. The structure of a ball bearing is shown in Figure 2. When there are faults in bearings, as the balls pass through the defective spot in the inner race or outer race, or as the ball with a defect rolls between the inner and outer races, periodic impulses are generated. And that impulses make the bearing vibrate in its natural frequency (called also ringing frequency) modulated by pass frequency at which the impulses are generated. Typically, the natural frequency or ringing frequency of the bearing is above 1 kHz.

For each type of faults in a bearing pass frequency can be calculated as follows.

- inner race defect

$$f_i = \frac{Zf_r}{2}(1 + \frac{d}{D}\cos\alpha) \qquad (2)$$

- outer race defect

$$f_o = \frac{Zf_r}{2}(1 - \frac{d}{D}\cos\alpha) \qquad (3)$$

- ball defect

$$f_b = \frac{f_r D}{d}(1 - \frac{d^2}{D^2}\cos^2\alpha) \qquad (4)$$

where, Z is the number of balls in the bearing, f_r is rotating frequency, D is the diameter of the pitch circle, and α is the contact angle in radian.

In order to generate signals from various abnormalities, a test bench is made as shown in Figure 3. In the left end a three-phase induction motor of 5.5kW lies which is powered by an inverter, and in the right end a generator lies which is used for a load. In the motor side, there is a fly wheel of about 13kg with 16 holes which are made for easy attachment and removal of the payloads in making unbalances. A gear box lies in the generator side for the monitoring of the faulty gear signals.

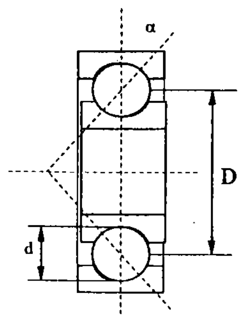

Figure 2: Structure of a ball bearing.

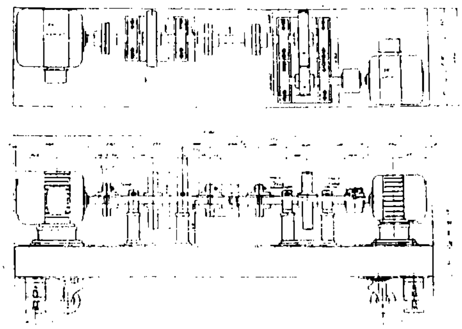

Figure 3: The test bench used in this experiment.

III. Signal Processing

In order to get vibration signals from the machine, there must be a vibration sensor. There are various vibration sensors such as eddy current probe for position, moving element for velocity, and accelerometer for acceleration. In this experiment we use piezoelectric accelerometer. Accelerometers are a popular transducer for vibration measurements and also to record earthquakes. The main advantages of the piezoelectric accelerometer are compactness, ruggedness, good temperature resistance, high sensitivity, and high frequency range. Although accelerometers, hower, provide an excellent mechanism for collecting vibration data, they are also highly sensitive to noise. So, the use of piezoelectric accelerometer requires cautious treatments. In this experiment, Piezoelectric accelerometer (PA-01) was used to detect the vibration of a machine. Its sensitivity is $50mV/g$ and the frequency range is $3 \sim 7500Hz$.

The signal processing schemes are different depending on the vibration frequency range. In studying abnormality in the low frequency and gear diagnosis, the velocity signal, i.e. integral of the acceleration signal, is used in the diagnosis of faults. The acceleration sensor is connected to an amplifier specially designed for low noise cable. In order to eliminate the possible DC component which can be caused by an offset voltage in OP amps, we make use of a high-pass filter. Then, we get a velocity of the vibration by integrating after filtering. In order to avoid aliasing due to high frequency components, a low-pass filter with the cut-off frequency of 1kHz is used before

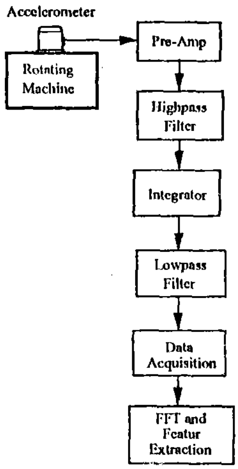

Figure 4: Block diagram of low frequency signal processing.

sampling. The output signal of the low-pass filter is fed into a ADC whose data bits are connected to a 486DX PC data bus. Figure 4 shows the block diagram of low frequency signal processing scheme.

Sampling frequency for the low frequency range diagnosis was chosen at 1 $\sim$ 2kHz and the number of sampled data is 6144. Then, we divide the sampled data into 2 segments. Each segment has 4096 data and overlaps with the nearby ones by one half of its length.

Then each set(segment) of 4096 data is multiplied by Welch window and transformed into frequency domain by FFT, i.e.,

$$D(k) = \sum_{j=0}^{N-1} w(j)c(j)e^{2\pi jk/N}, \qquad k = 0, \ldots, N-1 \quad (5)$$

$$w(j) = 1 - \left(\frac{1 - 0.5(N-1)}{0.5(N+1)}\right)^2 \equiv \text{"WelchWindow"}, \quad (6)$$

where, $N = 4096$ in this experiment and $c(i), 1 \le i \le N$, denotes the time-domain data in a segment. Also, the power spectrum is obtained by

$$P(0) = \frac{1}{W_{ss}}|D(0)|^2$$
$$P(k) = \frac{1}{W_{ss}}\left[|D(k)|^2 + |D_{N-k}|^2\right], \; k = 1, 2, \cdots, \left(\frac{N}{2} - 1\right)$$
$$P(\frac{N}{2}) = \frac{1}{W_{ss}}\left|D(\frac{N}{2})\right|^2$$

where, W_{ss} stands for *window squared and summed*, $W_{ss} \equiv N\sum_{j=0}^{N} w(j)^2$.

After obtaining 2 sets of power spectra, average them out, and we denote the averaged power spectrum by $\bar{P}(0)$, $\bar{P}(1)$, $\cdots$, $\bar{P}(2048)$. For a given sampled data, this kind of overlapping method is known to give a smaller variance than the nonoverlapping method[2].

As mentioned, when a bearing has some faults, ringing frequency is modulated by pass frequency that carries information about faults. So, demodulation process is necessary in signal processing. Vibration signal from bearing is collected by using an accelerometer placed in the radial direction to the loading of the bearing. The accelerometer is screwed onto a flange, and the flange, in turn, is stuck to the rolling element. Then, these data are fed into band-pass filter, which cuts off below 1 kHz and above 10 kHz. Those cut-off frequencies are chosen, because ringing frequency is above 1 kHz, and principle mode of vibration, mode 2 or mode 3 is below 10 kHz. In case of the bearing tested in this experiment, vibration frequency of mode 2 and 3 are 2.122 and 6.002 kHz, respectively. Following the band-pass filter there are absolute value circuit and envelope detector. This final output is used as input to the ADC. Data for bearing are sampled at 3 kHz and the number of data is 6144. The next is the same procedure as the low frequency range. Figure 5 shows this processing scheme.

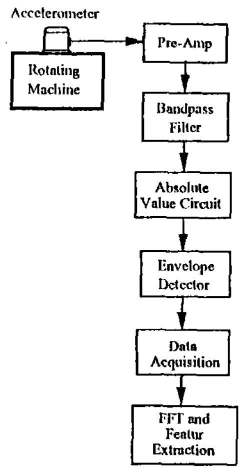

Figure 5: Block diagram of high frequency signal processing.

IV. Feature extraction and Diagnosis

A. Feature extraction

After obtaining the power spectrum of vibration signal, we should make it adequate for the input into the neural net. If the number of input nodes are too large, training is too slow to use in practice. The power spectrum may contain redundant data which have no useful information in the diagnosis. One method for reducing input data size is to use recirculation network as in [6]. But if we use that network for data compression in this case, the number of nodes in input layer becomes 2048, too large for use. Here we discuss different method that uses feature extraction for the smaller input space using the knowledge of vibration characteristics of the machine. As operating condition such as rotor speed changes the power spectrum varies, so we should make feature vector independent of operating condition. In order to do this task, frequency normalization and magnitude normalization are used here. Because the vibration spectrum varies proportional to the rotating speed of the machine, frequency normalization is achieved by dividing power spectrum by the frequency of the rotating speed of the machine, f_r.

In the low frequency range we know that $f_r, 2f_r$, and $3f_r$ frequency components are very sensitive to the faults such as misalignment, unbalance, bolt loosening, and so on(see Figure 8–10). We use these components and their neighborhood as the feature vector in the low frequency range. This is done by multiplying three Hanning window with width of $2/5f_r$, height of 1, and center of each at $f_r, 2f_r$, and $3f_r$, respectively, and then add them to make three-dimensional vector. The forth element is used to discriminate between signatures with vibration levels considered normal and signatures of possibly faulty components. This can be done by comparing power of the characteristic frequency with that of the other frequency range. The value of this element is binary, a one indicates absence of a fault and a zero indicates a possibly faulty signature. This vector is normalized in magnitude to unit length in Euclidean norm.

When there are faults in bearing, the frequency components such as f_i, f_o, f_b, become dominant. For example, when a bearing has fault in inner race, frequency component at f_i grows large. Thus we extract feature from frequency components f_i using Hanning window with width $2/5f_r$. This procedure is done also with f_o and f_b. Like the method in the low frequency range, the forth element of the feature vector is the ratio of the energy of the fault frequency to that of the others. The vector which has four components is normalized to unit length and this vector is used as the input vector of the neural network for the bearing diagnosis.

In the diagnosis of gear faults, the mesh frequency of the gear becomes very important clue. As mentioned previously, if there are faults in gear element, the frequency components f_m and its side bands $f_m \pm n f_r$ become larger than that of normal operation, especially the side bands (See Figure 11–12). Thus we use $f_m \pm n f_r$, $n = 0, 1, 3, 4$, components as feature vector components. And this vector is normalized to unit length.

B. Diagnosis using BPN

In this experiment we use back propagation neural network for diagnosis. Diagnosis scheme is shown in Figure 6. The feature vector is used as the input to the BPN to identify which fault has occurred. Three BPN's are used in the diagnosis and each neural network is trained for low frequency range diagnosis, the gear diagnosis, and the bearing diagnosis, respectively. The structure of the three BPN's have similar form in Figure 7. The BPN used for low frequency range diagnosis and the bearing diagnosis has 4 input nodes, 6 nodes for each hidden layer, and 4 output nodes. The BPN used for the gear diagnosis has 5 input nodes, 6 nodes for first hidden layer, 5 nodes for second hidden layer, and 2 output nodes. The nonlinear function used in each node is the standard sigmoidal function.

The BPN for the low frequency range diagnosis can identify 4 different faults; normal(N), unbalance(U), misalignment(M), and bolt loosening(B). The BPN for the gear diagnosis identifies normal operation(N) and gear faults(F). The BPN for bearing diagnosis identifies normal(N), inner race fault(I), outer race fault(O), and defect in ball(B).

V. Test Results

Diagnosis using BPN was performed by using the test bench in Figure 3. Bearings' type number under test is 6008ZZ and the parameters are in Table 2. These parameters can be found easily in the manual of the machine and must be entered by human operator to diagnose the bearing. Using those parameters in equations (2) – (4), we get pass frequencies $f_i = 6.82876 f_r$, $f_o = 5.17124 f_r$, and $f_b = 6.67335 f_r$. To diagnose machine, we must measure or estimate the rotational frequency f_r. f_r can be estimated by measuring peak amplitude in the spectrum in an appropriate range as in [10]. In this case frequency resolution must be fine enough for the accurate estimation of f_r such that no faulty diagnosis should be made. In the low frequency range diagnosis, the resolution of the spectrum is about 0.25Hz. Furthermore, this technique requires f_r component is actually the peak component in the interested range. This is not satisfied in all cases. So we use encoder for f_r measurement by attaching on the one end of the rotor. The training of the BPN

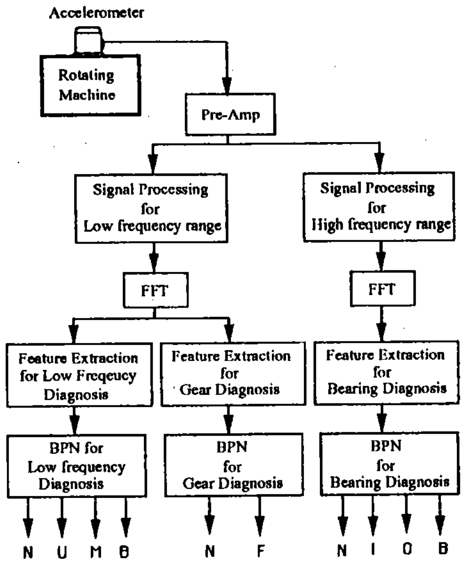

Figure 6: Block diagram of diagnosis scheme.

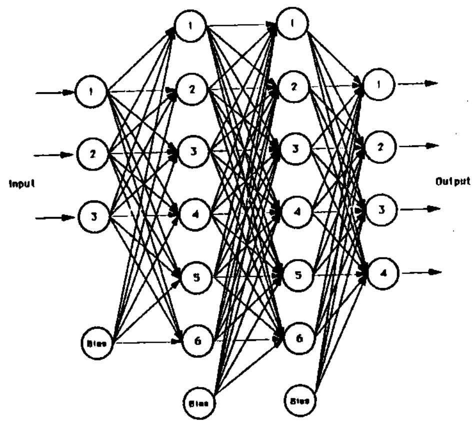

Figure 7: Structure of the BPN used in diagnosis.

Parameter	D	d	Z	α
Value	54 mm	7.9375 mm	12	20^o

Table 2: Parameters of the tested bearing(6008ZZ).

was performed such that only one output node could produce 1 and the others 0 according to each fault and standard gradient decent learning rule algorithm with momentum was used. The output vectors for training in low frequency range diagnosis is shown in table 3 and output vectors for the other diagnoses are defined in similar way. As the training data set, we used vibration signals from the test bench by operating normally and by changing faulty components. The training data was classified correctly in the diagnosis, and is not included in the calculation of accurate diagnosis rate.

Fault type	Output vector
Normal	(0.97, 0.03, 0.03, 0.03)
Unbalance	(0.03, 0.97, 0.03, 0.03)
Misalignment	(0.03, 0.03, 0.97, 0.03)

Table 3: Desired output vectors of the BPN for low frequency diagnosis.

We have applied the minimum distance rule to the neural net outputs in determining the fault occurred, i.e., we measure the distance between a neural net output and the four desired output vectors, and determine one as the corresponding result if the distance is the smallest. In low frequency range, we trained neural network to diagnosis normal, unbalance, and misalignment operation and obtained 100% accurate result. In gear diagnosis, we diagnosed normal or fault and the result is about 70% accuracy. In bearing diagnosis, we diagnosed normal or inner race defect and the result is 100% accuracy.

Figures from 8 to 12 show power spectrum of each operating mode used in this experiment. The test data were collected in the condition of various rotating frequency and in the low frequency range diagnosis test, the severity of the fault was also altered.

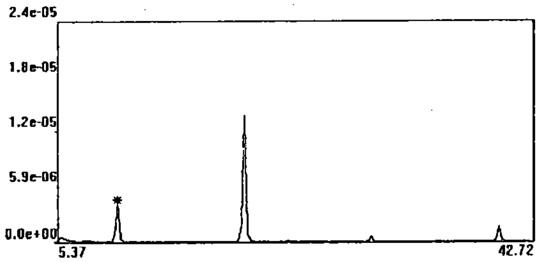

Figure 8: Power spectrum of normal operation in the low frequency range.

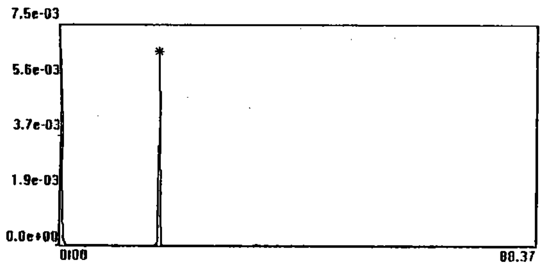

Figure 9: Power spectrum of unbalance in the low frequency range.

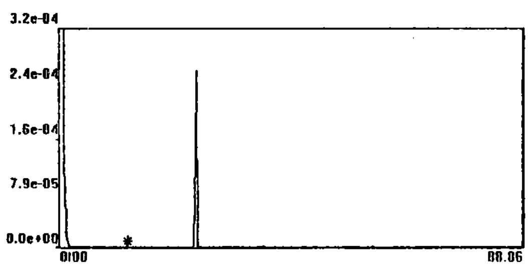

Figure 10: Power spectrum of misalignment in the low frequency range.

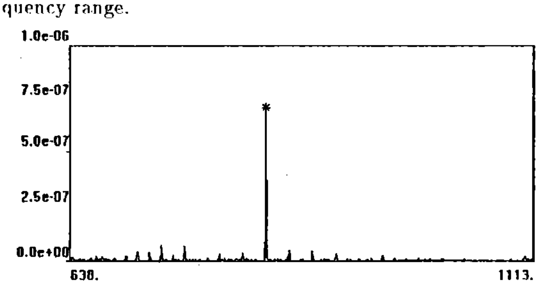

Figure 11: Power spectrum of normal operation of gear.

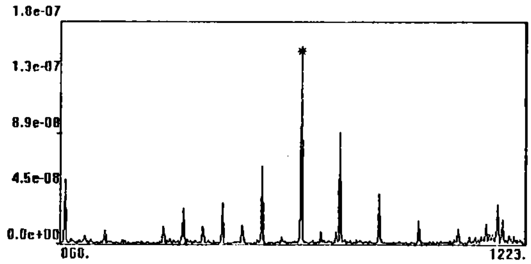

Figure 12: Power spectrum of faulty gear.

VI. Concluding Remarks

In this work, a neural-network-based methodology for developing fault diagnosis system for rotating machines was considered. In low frequency rage, we extracted feature vectors from the vibration signals due to rotor unbalance and axis misalignment and trained the BPN using these vectors. Then we extracted feature from arbitrary vibration signals and applied it to the trained neural network to diagnose the rotating machine. In similar way, we discriminated faults in bearing and gear. Although we used the data collected from the test bench to generate data that were used in training, it is also possible to use simulation data to train the network with the help of *a priori* knowledge of vibration characteristics. There needs more work in order to handle the complex abnormalities which are more common in the real situation, i.e., the abnormalities which are caused by more than one trouble.

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