Fault Diagnosis System for Machines Using Neural Networks*

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This research is concerned with the fault diagnosis for machines using neural networks. Generally, it is difficult to diagnose machine's fault by the conventional technique. In this research, two new fault diagnosis systems are proposed which one diagnoses a fault based on behavior of the object system, and another diagnoses a fault based on power spectrum of the object system. In the former, when an object system is a normal state, the system identification is performed by the neural networks. The diagnosis system detects a fault by finding the behavior's gap between the state of the real system and the identified normal one, and also the fault part is specified by fault diagnosis neural network. In the latter, neural network learns power spectrum of both the normal and fault states for the object. When a fault occurs, fault part is diagnosed by fault diagnosis neural network based on power spectrum. Finally, through simulation and experiment, the effectiveness of proposed fault diagnosis systems is verified.

Key Words: Neural Network, Learning, Machine Fault, Fault Diagnosis, System Identification, Power Spectrum

1. Introduction

At present, every kinds of plants have been highly automated and precisely produced. However, it is impossible to avoid fault in these systems. When a fault occurs, the fault must be detected as soon as possible. Because, if the machine runs at an abnormal condition continuously, it may result in heavy loss and even loss of human lives. Therefore, the reliable fault diagnosis system may be required.

The conventional fault diagnosis has been, until now, performed by skilled engineers with their experiences and technical knowledge. For example, one fault causes one symptom. It is no doubt to require the higher reliability for fault diagnosis system, because further full-automation may be anticipated in the future. But, it is not easy to detect fault automati-

cally and to know the part of fault. Especially, it is difficult to detect a fault by conventional methods based on numerical model^{(1),(2)}. Also, when the fault part is specified, the pattern matching is only used between a symptom and the fault. In this case, the problem is how to generate matching patterns. Furthermore, the generation of the matching patterns becomes difficult for many fault patterns.

In this paper, a fault diagnosis method using neural network is proposed. The neural network has an ability to memorize information from the outside in its inside. Therefore, using neural networks, it is possible to memorize system features in the network by reiterating learning for the identification of non-linear system. A lot of studies are performed for identification of non-linear system⁽³⁾⁻⁽⁸⁾. Also, for the fault diagnosis, it is possible to memorize both symptoms and matching patterns by learning the data of fault.

This study proposes two kinds of method of fault diagnosis system. One method is fault diagnosis system using system identification. This method diagnoses a system by comparing real data with normal data which were learned by the neural network. The other method is a diagnosis system using a spectrum data which were obtained from the object system. Each fault diagnosis systems can be applied

* Received 15th November, 1999. Japanese original: Trans. Jpn. Soc. Mech. Eng., Vol. 65, No. 632, C (1999), p. 1498-1504 (Received 17th July, 1998)

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to any mechanical systems, and it is possible to detect the fault part from behavior. The feature of this method is that these diagnosis systems don't need a knowledge of the object system's numerical model and so on. Through simulation studies, the effectiveness of proposed fault diagnosis system is verified, and the practical example is reported of applying this method to actual wood slicer machine processor is reported.

2. Fault Diagnosis System

2.1 Fault diagnosis system using system identification

2.1.1 System structure The structure of fault diagnosis system using system identification is shown in Fig. 1. This fault diagnosis system has two types of neural networks, which are for system identification and for fault diagnosis. In Fig. 1, the neural network for system identification learns only the normal state of object system. In this system, inputs to neural network are external force $q(t)$, position of object system $x(t+1)$ and prediction value of normal state position $\hat{x}(t+1)$. These variables are inputted to neural network every 1-sampling. If some fault occurs in real system and the system behavior changes, a gap between $x(t+1)$ and $\hat{x}(t+1)$ is generated. In this system, based on a gap of these two input values, it is diagnosed a fault and specified a fault part on real time.

2.1.2 Neural network for system identification

The neural network for system identification learns every 1-sampling mapping of time series data observed from object system. The structure of neural network is shown in Fig. 2. This neural network is hierarchical, which has input layer (4-unit), hidden layer (20-unit) and output layer (1-unit). Inputs to neural network are external force $q(t)$ and position $x(t)$ at time t and external force $q(t-1)$ and position $x(t-1)$ at time $t-1$. The output from neural network is a prediction value of position $\hat{x}(t+1)$ at time $t+1$. Here, the learning for coefficients of connection weight is performed by back propagation method⁽⁹⁾ with rms (root mean square) error of Eq. (1) as an evaluation of learning. When rms error becomes

Fig. 1 Structure of fault diagnosis system using identification method

below 0.002, the learning ends.

$$rms = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - d_i)^2}, \quad (1)$$

where y_i is an output from neural network, d_i shows a teaching signal. Here, a teaching signal is used a position obtained by numerical calculation. Also, for system identification N shows the numbers of learning data, i a learning data number.

2.1.3 Neural network for fault diagnosis

The structure of neural network for fault diagnosis is shown in Fig. 3. This neural network is hierarchical, which has input layer (3-unit), hidden layer (20-unit) and output layer (2-unit). Inputs to neural network are external force $q(t)$ at time t , position $x(t+1)$ and output of network for identification $\hat{x}(t+1)$ at time $t+1$. Outputs of neural network are diagnosis results for each components. Since the diagnosis system diagnoses for spring and damper in this paper, the neural network has two units in output layer, i.e. one is for spring and the other for damper. The learning of neural network is performed by back propagation method. The teaching signal is 0 for the normal condition and 1 for the fault condition.

2.2 Fault diagnosis system using spectrum

2.2.1 Structure of system The structure of fault diagnosis system is shown in Fig. 4, which is

Fig. 2 Neural network for identification

Fig. 3 Neural network for fault diagnosis

Fig. 4 Structure of fault diagnosis system using spectrum.

based on spectrum of a time series data. This system is constructed by both FFT analyzer which converts time series data to spectrum and the diagnosis neural network. In Fig. 4, FFT analyzer calculates the frequency spectrum $F(k)$ by FFT (Fast Fourier Transform) shown in Eq.(2), and it outputs the power spectrum which takes its square of the absolute value.

$$F(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi kn/N} \quad (k=0, \dots, N-1) \quad (2)$$

where, $f(n)$ shows time series data obtained from object system. The relation concerning with sampling time Δt , sampling period T , and frequency resolution $\Delta\omega$ [Hz] is given by

$$T = 1.0/\Delta\omega \quad (3)$$

$$\Delta t = T/N \quad (4)$$

In the simulation, we set, $N=1024$, $\Delta\omega=0.1$ [Hz], and then the sampling period is $T=10$ [s] and sampling time $\Delta t=9.8 \times 10^{-3}$ [s]. After first sampling period, power spectrum is calculated, and it is inputted to neural network for diagnosis. Then it can be diagnosed a fault from its output. After that, it can be calculated spectrum and inputted to diagnosis neural network every 1-sampling. At result, we diagnose the fault and detect the fault part on real time by using spectrum.

2.2.2 Neural network for fault diagnosis

The structure of neural network for fault diagnosis is shown in Fig. 5. This neural network is hierarchical which has input layer (40-unit), hidden layer (20-unit) and output layer (2-unit). Inputs are spectrum data from 0.1 Hz to 4.0 Hz which are obtained from FFT analyzer, and then its output corresponds to diagnosis result. The learning of connection weights is performed by back propagation method with rms (root mean square) error as Eq.(5). When rms error becomes below 0.01, the learning ends.

$$rms = \sqrt{\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^L (y_{i,j} - d_{i,j})^2}, \quad (5)$$

where $y_{i,j}$ is the output from neural network, and $d_{i,j}$ shows a teaching signal, which is 0 if the part is normal and 1 if it's fault. Also, N shows a numbers of learning data, and i a learning data number. Furthermore, N and L show the number of learning data and output layer, respectively and i and j a learning data number.

Fig. 5 Neural network for fault diagnosis

3. Simulation Studies

3.1 Fault diagnosis system

As an object system of fault diagnosis, it's considered Duffing oscillation model with the following dynamics,

$$m\ddot{x} + c\dot{x} + kx + ax^3 = q(t) + w(t) \quad (6)$$

where, x is a displacement and m a mass of object. The $w(t)$ is a noise added to system (which is assumed to be a white gaussian noise) and $q(t)$ an external force which is given by $q(t) = q \cos \omega t$. The c is a coefficient of viscosity and $kx + ax^3$ a force of spring.

In this study, the fault diagnosis is performed concerning with a spring and damper of this oscillation model. It is assumed that a fault may be generated by the change of K , a and c in Eq.(6).

3.2 Fault diagnosis using system identification

3.2.1 Learning of neural network for identification In Eq.(6), the initial conditions and parameter values of normal state are shown such as,

$$m=1.0, k=2.0, a=50.0, c=1.0, q=1.0, \omega=2.0$$

$$x(0)=0.01, \dot{x}(0)=0.01$$

The neural network for identification learns this state as a normal condition. The learning is performed every 1-sampling; The one trial is 50[s] and the sampling time 0.25 s (learning data number is $N=200$). In this case, as the rms error, by the evaluation function of Eq.(1) becomes 0.0017 at 5800 trial number, the learning is finished. An example of the identification result is shown in Fig. 6. In Fig. 6, as the output of a neural network (solid line) is a good agreement with the one of an object system (dotted line), the identification of Duffing oscillation model is well performed. This neural network is used for fault diagnosis.

3.2.2 Learning of neural network for diagnosis

It's assumed that the condition of spring is changed

Fig. 6 Identification result

Fig. 7 Fault behavior (Spring's fault)

Fig. 8 Fault diagnosis result (Spring's fault)

from normal state to fault one at 20 s, which is changed to $k=1.0$ and $\alpha=25.0$. Similarly, it's assumed the fault condition of damper is changed to $c=0.4$ at 20 s. The neural network for diagnosis learns these two conditions 2 500 times.

Next, the diagnosis result for the learned fault condition is illustrated. Here, we assume that the system changes at 40 s to the fault condition of spring, that is, $k=1.0$ and $\alpha=25.0$. The system behavior of the object Eq. (6) is shown in Fig. 7 and the diagnosis result in Fig. 8, respectively. From Fig. 8, the output of neural network for diagnosis becomes 1 after 40 s, and then the diagnosis is well performed. Also, it's confirmed the fault diagnosis for damper is well performed, too.

(a) Normal state

(b) Spring's fault

(c) Damper's fault

Fig. 9 Learning data

3.3 Fault diagnosis using spectrum

In this section, the fault diagnosis using spectrum is explained. It is assumed that each parameters of Eq. (6), initial conditions of the normal and the fault states of both spring and damper are set the same values as section 3.2.2. Then, the spectrums are calculated on each conditions. It's shown the figures of spectrum for learning in Fig. 9. While a natural frequency of the object system is 0.1598 Hz on normal state, it becomes 0.15892 Hz on the fault state of spring. Also, though the resonance frequency doesn't exist on the normal state, it becomes 0.1135 Hz on the fault state of damper. In Fig. 9, the peak value of spectrum is at 0.3 Hz for both normal and abnormal state, whose peak values are 6.00×10^3 in normal state, 9.27×10^3 in abnormal one of spring and 5.97×10^3 in

Fig. 10 Diagnosis result (Spring fault)

Fig. 11 Fault behavior (Spring's fault)

abnormal state of damper. According to the change of states in the object, the spectrum values and their shapes are changed. The rms errors given in Eq.(5) becomes 0.007 at 9 500 trial number and the learning is finished. The fault diagnosis results for learned states are explained.

First, it is assumed that the spring fault may be changed from normal state to fault one at 40 s, that is, to $k=1.0$ and $\alpha=25.0$. The diagnosis result is shown in Fig. 10. The output of neural network for diagnosis becomes 1 after 40 s in Fig. 10, and then the diagnosis is excellently performed. Also, it's confirmed that the fault diagnosis for damper is well performed, too.

3.4 Diagnosis for unlearned fault pattern

3.4.1 Fault diagnosis using system identification

The ability of fault diagnosis system is confirmed using learned connection weights for unlearned fault conditions of both spring and damper. It is assumed that the fault condition of spring is changed at 40 s from normal state to fault state of $k=1.5$ and $\alpha=25.0$ (the learned fault condition is $K=1.0$, $\alpha=25.0$). The behavior of the object system is shown in Fig. 11. Also, the diagnosis result is shown in Fig. 12. From Fig. 12, the output of neural network corresponding to spring becomes 1 after 40 s. Then, it can be verified that the fault diagnosis for unlearned state is well performed, too.

Next, it is assumed that the fault condition of damper changes to $c=0.6$ at 40 [s] (the learned fault

Fig. 12 Fault diagnosis result (Spring's fault)

Fig. 13 Diagnosis result (Spring's fault)

condition is $c=0.4$). Similarly, it is confirmed that the fault diagnosis is well performed.

3.4.2 Fault diagnosis using spectrum Similarly to section 3.4.1, it is assumed that the spring condition is changed from normal state to fault state $k=1.5$ and $\alpha=25.0$ at 40 [s] (the learned fault condition is $K=1.0$, $\alpha=25.0$). The diagnosis result is shown in Fig. 13. The output of neural network corresponding to spring becomes 1 after 40 [s], it can be said that the fault diagnosis on unlearned condition is excellently performed, too.

Next, it is assumed that the condition of damper changes to $c=0.6$ at 40 [s] (learned fault condition is $c=0.4$). Then, it is similarly confirmed that the fault diagnosis is well performed.

4. Effect of Noise

Generally, a noise or disturbance exists in the operating environment such as factories. The fault diagnosis must be performed exactly in such environment. Then, supposing that a noise is impressed to the signal obtained from an object system, the influence on the fault diagnosis system is examined.

In order to examine the disturbance influence to fault diagnosis system using system identification, it is assumed that a white gaussian noise is added to the object system, as the observation noise. Here, a diagnosis experiment is performed for a spring fault under the same condition as Fig. 7. This result is

(a) Output for spring

(b) Output for damper

Fig. 14 Fault diagnosis result

Fig. 15 Diagnosis result (Spring's Fault)

shown in Fig. 14. In this figure, the output corresponding to a spring in the diagnosis neural network becomes 1 after 40 sec, and then the fault can be detected. But, the output corresponding to damper is disturbed by disturbance, and then it might give an influence to fault diagnosis. Next, the diagnosis result using spectrum is shown in Fig. 15. As the output corresponding to a spring in the neural network for diagnosis becomes 1 after 40 sec, the diagnosis is well performed. Also, as the output corresponding to a damper becomes 0, the detection of fault part is well performed.

By comparing two fault diagnosis systems proposed in this paper, the following things can be verified. The diagnosis system using system identification can be sensitively affected by the disturbance. Then, it is difficult to diagnose precisely by a

week noise with S/N ratio 30.5. On the other hand, the diagnosis system using power spectrum is not necessarily affected by the noise. Then, it can be performing diagnosis more exactly than the diagnosis one using system identification, even if the same grade disturbance is added. In the fault diagnosis system using a spectrum, it is confirmed that it can perform diagnosis exactly up to S/N ratio 3.0. As the mentioned above, it turns out that the fault diagnosis using a power spectrum is suitable to the detection of a machine fault.

5. Fault Diagnosis of Wood Cutting Machine

In order to show the possibility of application to the diagnosis system using power spectrum proposed here, the fault diagnosis has been applied to an actual wood cutting machine. The wood cutting machine of a diagnostic object is a work machine which cuts down the 5 or 10 mm thin board for plywood from a raw timber. The cutting is a normal if the thin board is precisely cut, and, on the other hand, the cutting abnormal if the thin board is split or crack due to lack of a byte. Inputs to neural network are power spectrum data obtained from the sound signal, when the machine cuts the plywood. The fault diagnosis has been performed using the change of spectrum data. Here, it can be considered that the sound which a machine generates includes much information which shows the state of the machine, and then very useful as a diagnostic standard.

The data for the diagnosis records the operating sound of wood-cutting machine in the data recorder, and then this sound data is transferred to spectrum data using FFT analyzer. This converted spectrum data are preserved in computer, which are used as sample data for diagnosis.

First of all, 4 kinds of data which are 2 normal and 2 abnormal states are used for the learning of neural network. The spectrum data used for learning is shown in Fig. 16, where (a) and (b) are normal states, (c) and (d) abnormal states. Here, the output of neural network shows 0 if the state is normal and 1 if the state abnormal.

Next, the diagnosis has been performed for unlearned spectrum data using neural network with already learned connection weights. The examples of unlearned data are shown in Fig. 17. Theses data are real data which are already discriminated normal or abnormal. In Fig. 17, it is obvious that every spectrum data obtained from machine aren't uniform for both normal and abnormal states. Examples of diagnosis result for 10 spectrum data are shown in Table 1. The discrimination of fault diagnosis has been, by trial and error, determined as follows. If the output of neural

Table 1 Diagnosis result for samples

No.	Signal State	Output from N.N	Diagnosis Result	No.	Signal State	Output from N.N	Diagnosis Result
1	Normal	0.0562	Normal	6	Fault	0.6607	Uncertain
2	Normal	0.0562	Normal	7	Fault	0.8740	Fault
3	Normal	0.0562	Normal	8	Fault	0.8981	Fault
4	Normal	0.0989	Normal	9	Fault	0.9939	Fault
5	Normal	0.4590	Normal	10	Fault	0.9263	Fault

Fig. 16 Learning data for wood slicer

Fig. 17 Samples of spectrum data for wood slicer

network is less than 0.4, it means normal condition, if bigger than 0.7, it means abnormal one, and others are uncertain. From the result of Table 1, it is verified that the precise diagnosis has been performed for wood slicer machine. By these results, it has been shown that this fault diagnosis system proposed here has the possibility of application to practical machine system.

6. Conclusion

In this research, two kinds of fault diagnosis system are proposed using neural network. Through simulation studies, the effectiveness has been examined. Furthermore, through experiments, the utility of this fault diagnosis system has been verified. The results are summarized below.

(1) The fault diagnosis system proposed here has been applied to Duffing oscillation system, and it is shown that it is possible to detect the fault part for the unlearned fault pattern of Duffing's spring and damper.

(2) The effect of noise to diagnosis system has been considered. It has been clarified that the influence of disturbance, in the spectrum data, is smaller than time series data of the system with a noise disturbance, and precise diagnosis has been

performed.

(3) The fault diagnosis system using spectrum data has been applied to real wood slicer machine, and it is verified that the fault diagnosis can be performed by using proposed method.

Though there exist some uncertain results for the diagnosis of practical system, it can be verified that the proposed diagnosis system has a sufficient utility.

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