Fault Diagnosis for Electro-Mechanical Control System by Neural Networks

Takashi Torigoe, Masami Konishi, Jun Imai, and Tatsushi Nishi
Department of Electrical and Electronic Engineering
Okayama University
3-1-1 Tsushimanaka, Okayama, 700-8530, Japan
konishi@elec.okayama-u.ac.jp

Abstract

In this paper, neuro based intelligent diagnosis methods for electro-mechanical control system are proposed. A self organizing map neural network (SOM) is used to classify measured data of the target system as a qualitative diagnostic method.

Besides of the above procedure, it is expected to attain more efficient maintenance by a quantitative estimation of failure. For the purpose, new method is proposed using a hierarchical neural network (HNN). In the method, classified results by SOM are processed for the quantitative diagnosis. Hierarchical neural network can identify inner structure of the relations between failure causes and its results that enables a quantitative diagnosis.

Keywords : neural network, Self organizing map, fault diagnosis

1 Introduction

When some failure occurs in a mechanical system, diagnosis of the system is to be performed. Then, maintenance or repair action is carried out recovering the system performance to its normal state. As it is impossible to acquire whole internal information of the system, it is usual to analyze output data of the system for the estimation of failure causes.

Traditionally, fault diagnosis is governed by human experts with plenty of experiences and knowhow. In these days, mechanical systems are becoming more complex and enlarged in its scale together with its control system. So it becomes necessary to develop new technologies for fault diagnosis not only in a qualitative but also a quantitative manner coping with the needs for automatic diagnosis of complex control systems.

In this paper, SOM[3] method is used for qualitative fault diagnosis in a electro-mechanical control system. Measured data of a system is input to SOM, and classified to particular nodes of SOM. The fault of the system is diagnosed qualitatively from geometrical information of the classified node.

Addition to that, a quantitative diagnosis method using HNN[2, 4] is described. The inputs to HNN are measured data and geometrical information of classification by SOM. The HNN describes correlation between input data and internal fault of the target system. Through learning, the HNN model is updated so as to generate correct value of the internal fault state quantitatively.(Fig. 1)

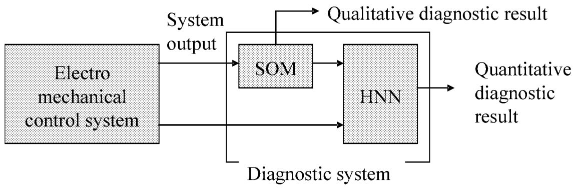

Fig. 1 Diagram of estimation system

First, the looper height control system[1, 5, 6] is selected as a target system of the proposed diagnostic method. After that, diagnosis of an induction motor and that of a robot arm control system are made to verify the versatility of the proposed method.

2 Diagnosis of looper height control system

2.1 The looper height control

The looper height control system consists of looper height detection, PID controller and feedback operation. The block diagram of a looper height control system is shown in Fig. 2.

Here, $G(s)$ represents the transfer function of looper dynamics. There is a time delay in measurement after the output of $G(s)$. This time delay element is a representation of detection delay.

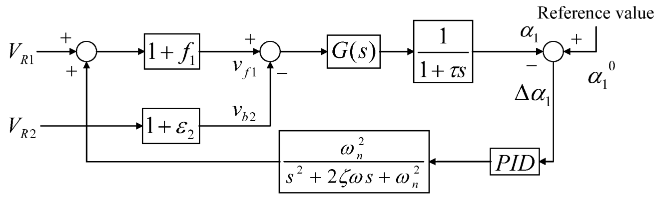

Fig. 2 Block diagram of a looper height control system

Based on detection of the looper height, V_{R1} is manipulated by PID control. There are 2nd order time delay element to manipulate V_{R1}, because of force transmission by torsion.

2.2 Waveform of looper angle

Here, the movement of looper height is simulated when the characteristics of looper height control system in the hot strip mills are changed.

In this paper, 3 factors (K_P, τ, ω_n) are concerned as the characteristics which will be changed.

The looper height is contolled by tuning the proportional gain K_P. The other two elements are internal values of the looper control system. Time delay τ of looper height sensing becomes large with the progression of deterioration in sensing euqipment. Natural angular frequency ω_n becomes small according to fatigue or deterioration in transmission system. These states are abnormal necessary to be found. Where, normal state means that time delay of the element is short time, and abnormal state means that time delay of the element is long time

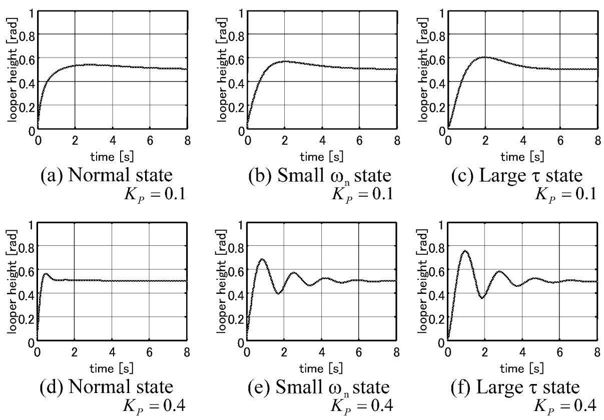

Fig. 3 Waveform of looper angle

The looper height waveforms when the K_P is changed are shown in Fig. 3(a), and Fig. 3(d). There is an overshoot when the K_P is large.

The looper height waveforms when the K_P is changed when ω_n is small are shown in Fig. 3(b), and Fig. 3(e). The oscillation of looper height waveform is enlarged by change of ω_n or τ in comparson with Fig. 3(d). However, By tuning the K_P, oscillation of the waveform is reduced.

3 Classification of looper data

When human get data, it is compared with past data, and result of the comparison leads the conclusion. However, it is difficult to execute those procedure automatically. In this section, the classification method by using SOM neural network is proposed.

3.1 Self Organizing Maps(SOM) N. N.

SOM[3] is a multidimensional scaling method projecting input data space to lower dimentional output space. Typically, output data space is made as 2-dimension. Thus, input data space is visualized into 2-dimensional plane.

Here, the condition in the application of SOM for the classification of looper height waveforms. The looper height waveform is analyzed by wavelet transform, the feature of the waveform is emphasized to wavelet coefficient which is 2-dimentional matrix. The classification method by SOM is applied to the matrix data.

An illustration of the classification is shown in Fig. 4. SOM is trained by a lot of waveforms generated by looper control system in various cases.

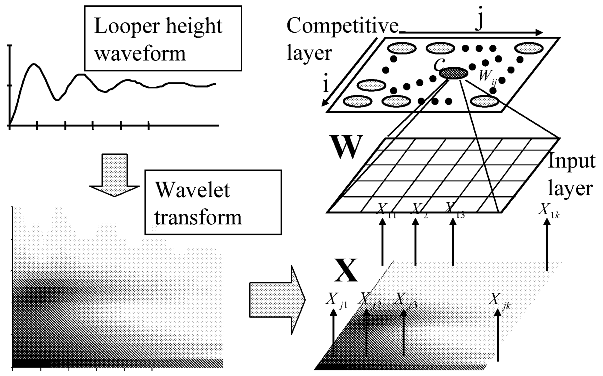

Fig. 4 Qualitative diagnosis by SOM

Where the input waveforms are analyzed by using wavelet transformation as a pre-processing. The number of training times is set to 10000. The number of training data is 250. Where, sampling period is $0.05[s]$ and sampling time is $5[s]$. The size of SOM N. N. in this case is 15×15.

3.2 Classified results (Qualitative diagnosis)

The classified ratio of each nodes in the SOM is described. The failure is considered at small ω_n value and at large τ value. In this case, for failure conditions, $\omega_n < 13$ and $\tau > 0.25$ are considered.

Fig. 5 shows classified results for normal conditions. Lines in Fig. 5 are contour lines corresponding to the ratios with which the data is recognized as normal state. The results in failure state are shown in Figs. 6, 8 respectively.

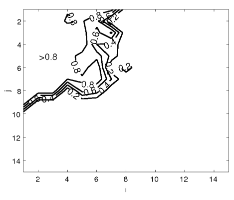

Fig. 5 Classified results of normal state

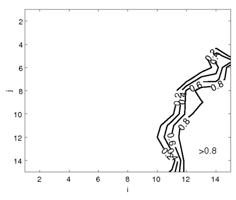

Fig. 6 Classified results of failure state

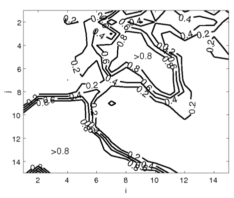

Fig. 7 Classified results of ω_n failure

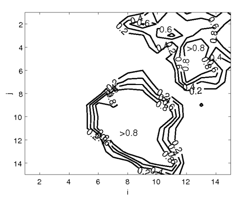

Fig. 8 Classified results of τ failure

These figures show that, data are classified in SOM separately according to the fault.

By classifying the wave form, the data is projected to the 2-dimensional plane. From the position of the plane, it is possible that diagnosis of waveform vibrations or estimation of failure causes qualitatively.

4 Quantitative diagnosis for hot rolling mills

As described above section, the qualitative estimation is made by using SOM. In this section, quantitative estimation method of failure state is described.

4.1 Hierarchical neural network

Neural network is a simplified model of the human brain. It consists of one or more artificial neurons. Therefore, it has the ability to learn and adapt. Also, there are many industrial applications. The hierarchical neural network (HNN) is one of artificial neural networks.[2, 4]

In this paper, the input of HNN is data which contains looper height waveform and classified results described in previous section. And the output of HNN is the parameters in the looper height control system, which provides the fault of the system. Structure of the HNN with the classified results is shown in Fig. 9.

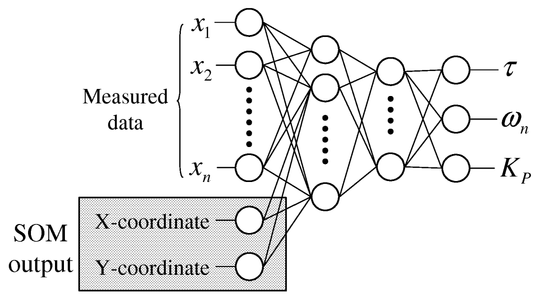

Fig. 9 Quantitative diagnosis by HNN

The HNN model with the classified results (22-40-10-3 4-layer NN) and HNN model without classified results (20-40-10-3 4-layer NN) are trained and compared. These models are trained 5000 times using 500 looper height waveform data which is ramdomly generated. After the training is finished, another 1500 waveform data is applied to these models.

As described above, In this paper, 3 factors are concerned as the characteristics which will be changed. K_P is a configurable parameters by human. Although, parameters to be estimated is τ, ω_n and K_P concerning tuning mistake.

4.2 Estimated results

Table 1 shows RMSE (Root Mean Square Error) of these estimated results. The results of the estimation are shown in Figs. 11, 10. The horizontal axis in these figures is actual parameters of looper height control system, And the vertical axis indicates the estimated parameters. If parameters are estimated with no error, dotted points in these figures are on a straight line.

Table 1 Error comparison

	τ	ω_n	K_P
without som	0.0089	0.50	0.020
with som	0.0044	0.36	0.0072

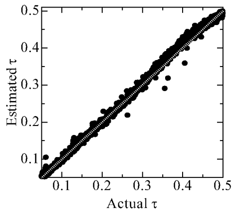

Fig. 10 Estimation result without SOM

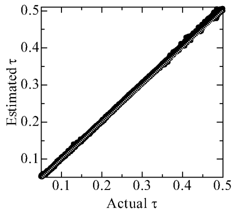

Fig. 11 Estimation result with SOM

Figs. 11, 10 shows that result of estimation using SOM are more accurate. This means that the estimation error is reduced by using SOM.

5 Further applications

5.1 Induction motor

To verify versatility of the proposed diagnostic methods, the estimation system is applied to induction motor. The physical model of induction motor is shown in Fig. 12

The induction motor consists of rotor and stator. In this case, fault of rotor bar is considered to diagnose. This time, the motor has six rotor bars ($R_{B1} \dots R_{B6}$), and three of them have possibility of fault. When the fault occurs, the electric resistance of the rotor bar is rise. So, it is intended that detection of the rotor bar resistance from angular velocity. Where, the resistance at normal state is $R_{B1} = 33.5[\Omega]$ in this time. Fig. 13 shows angular velocity of the induction motor, when the resistance R_{B1} is changed to $335[\Omega]$, $3350[\Omega]$.

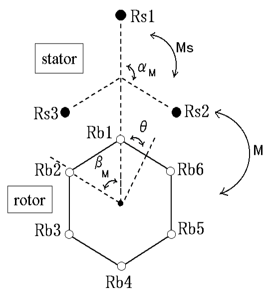

Fig. 12 Physical model of induction motor

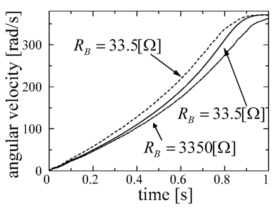

Fig. 13 Angular velocity

The rotor bar resistance is estimated from the angular velocity waveform shown in Fig. 13 using proposed estimation system consists of neural networks. The angular velocity is input to neural network system, and rotor bar resistance is learned as output of the system. Although, the rotor bar resistance is too large to learn as output of neural network, so the neural network learns the resistance as $\log R_{Bn}$. Table 2 shows RMSE of these estimated results. Fig. 14 is the result of R_{B2} estimation using normal neural network. Another estimation result using combined system is shown in Fig. 15.

Table 2 Error comparison

	bar1	bar2	bar3
without som	0.0673	0.0769	0.0670
with som	0.0608	0.0577	0.0597

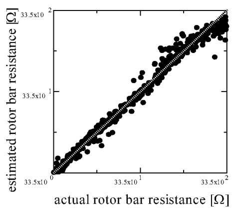

Fig. 14 Resistance of rotor bar #2

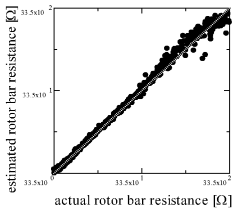

Fig. 15 Resistance of rotor bar #2 with SOM

These results show that estimation error is reduced by neural network combined system, and realized that the neural network system is applicable widely.

5.2 Robot arm

Next, the estimation system is applied to robot arm control system. The robot arm control system is shown in Fig. 16.

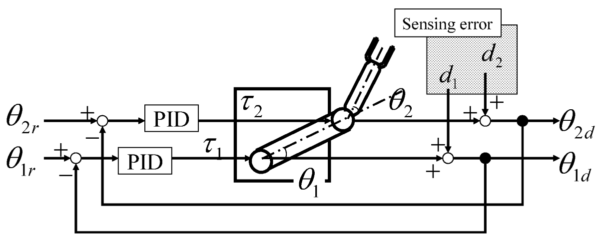

Fig. 16 Robot arm control system

The arm has two motors #1 and #2. The angle θ_n of motor #n are controlled to reference angle θ_{nr} by PID controller. Although, there are sensing error d_n in the part of measuring the θ_n. So, the measured θ_{nd} includes sensing error. Detection of

d_n from θ_{nd} is intended. An example waveform of θ_1, θ_2 are shown in Fig. 17. Sensing error d_1, d_2 are shown in Fig. 18.

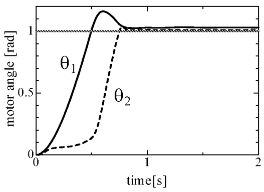

Fig. 17 Angles of arm

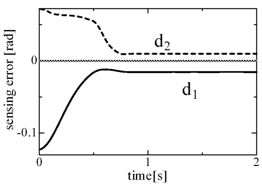

Fig. 18 Disturbances

Two estimation system is applied to θ_{1d} and θ_{2d}, and output the estimated d_1 and d_1 individually.

Figs. 19, 21 shows estimated sensing error by using normal neural network. Figs. 20, 22 are results by using proposed estimation system.

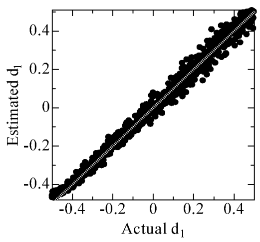

Fig. 19 Estimated d_1

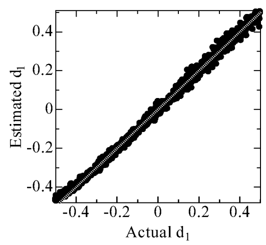

Fig. 20 Estimated d_1 with SOM

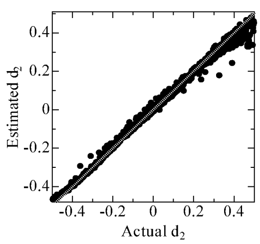

Fig. 21 Estimated d_2

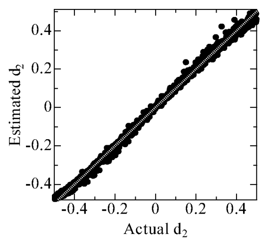

Fig. 22 Estimated d_2 with SOM

Table 3 shows RMSE of these estimated results. It is realized thatThe estimation system using SOM generates better results.

6 Conclusion

In this paper, a quantitative diagnosis method for electro mechanical control system by using SOM neural network is proposed. It is realized that fault of the looper height control system is detected by classifying the system data using SOM neural network model. Using the model, an accurate quantitative estimation of parameters in a looper controller can be made. similarly, effective diagnosis could be carried out for induction motor. Thus, not only detection of failure occurrence but also quantitative analysis of fault causes could be realized.

Table 3 Error comparison

	d_1	d_1
without som	0.029	0.024
with som	0.019	0.017

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