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ScienceDirect
Expert Systems with Applications 36 (2009) 49–56
Expert Systems with Applications
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A study of fault diagnosis in a scooter using adaptive order tracking technique and neural network

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Abstract

An expert system for scooter fault diagnosis using sound emission signals based on adaptive order tracking and neural networks is presented in this paper. The order tracking technique is one of the important approaches for fault diagnosis in rotating machinery. The different faults present different order figures and they can be used to determine the fault in mechanical systems. However, many breakdowns are hard to classify correctly by human experience in fault diagnosis. In the present study, the order tracking problem is treated as a parametric identification and the artificial neural network technique for classifying faults. First, the adaptive order tracking extract the order features as input for neural network in the proposed system. The neural networks are used to develop the training module and testing module. The artificial neural network techniques using a back-propagation network and a radial basis function network are proposed to develop the artificial neural network for fault diagnosis system. The performance of two techniques are evaluated and compared through experimental investigation. The experimental results indicated that the proposed system is effective for fault diagnosis under various engine conditions.

Keywords: Fault diagnosis; Adaptive order tracking; Neural network; Back-propagation; Radial basis function network

1. Introduction

Rotating machinery such as the internal combustion engine and transmission system of a scooter can be monitored by measuring the vibration and sound emission signals for early fault diagnosis. Some digital signal processing technique using vibration and sound emission signals already exist, such as visual dot patterns of sound emission signals (Shibata, Takahashi, & Shirai, 2000), wavelet analysis techniques (Lin & Qu, 2000; Wang & McFadden, 1996), and adaptive order tracking techniques (Lee & White, 1997; Vold & Leuridan, 1993). An order tracking technique based on a recursive least-square filtering algorithm in rotating machinery fault diagnosis was proposed in past research (Bai, Jeng, & Chen, 2002). The adaptive order tracking technique was used to extracting the order of features with vibration and sound emission signals for fault diagnosis. Order amplitudes figures were calculated with high resolution after the experiment and signal processing. In order to classify the mechanical system's fault, the order figures of various conditions must be carefully inspected. Unfortunately, it is hard to classify correctly by visual inspection and human experience because the features of some operation conditions are easily confused. In such condition, an expert system with intelligent classification is necessary to improve the recognition rate and fault diagnosis.

A number of expert system techniques have been proposed, such as fuzzy logic techniques (Huang, Yang, & Huang, 1997; Mechefske, 1998), and artificial neural network techniques (Subrahmanyam & Sujatha, 1997). In the present study, a technique of automatic fault diagnosis based on an artificial neural network is proposed.

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doi:10.1016/j.eswa.2007.09.015

An artificial neural network uses the massive simple connected artificial neurons to imitate the ability of a biological neural network. It obtains the information from the external environment or other artificial neurons, and performs the extremely simple operation. The above neurons will be combined and became a kind of neural network. The neural network must penetrate the training module and repeat to study, until all outputs can conform correctly to the optimal targets. The entire neural network has very high fault tolerance as it acts to solve the question in operation. If the input material combines a small amount of noise disturbance, the correctness of the neural network is still not affected in the process. It only gave a partial the material, then they may obtain the complete material. There is good performance of the associative memory and excellent fault tolerance. If there are more training samples and the difference is bigger, the abilities of the neural networks are stronger in the neural network. The neural networks may construct the non-linear model and accept the different types of variable as reference inputs. This technique has strong compatibility and good promotion.

Currently, many scholars have proposed variously kinds of neural network models which develop different algorithms to solve different demands. The common neural networks include back-propagation (BP) network (Li, Yu, Mu, & Sun, 2006; Randall & Robert, 2000), Hopfield network (Sun, 2002), radial basis function (RBF) network (Pulido, Ruisanchez, & Rius, 1999; Stubbings & Huter, 1999), and so on. In the present study, the BP neural network and RBF neural network are used for this intelligent fault diagnosis system. Both the BP and RBF neural network will train order curve figures of the scooter with normal and fault conditions under various operations for fault diagnosis. The effectiveness of the proposed system using two neural networks in scooter fault diagnosis is investigated and compared. The following sections describe the principle and experimental work of high resolution adaptive order tracking technique and neural networks in the scooter fault diagnosis system.

2. Fault diagnosis system with neural networks

The principle of adaptive order tracking technique has been previously proposed and described (Wu, Huang, & Huang, 2004; Wu, Wang, & Bai, 2007). The analysis of the order tracking with the sound emission signal and engine speed can be calculated as the amplitude of the frequency-modulation. The order amplitudes figures can be calculated with high resolution after signal processing. In order to classify the fault of scooter platform, the sound emission signal is transferred conveniently to fine feature as input for this diagnosis system. The neural network is a smart system that learns the knowledge in the fault diagnostic system. The principles of BP and RBF neural networks used in the present study are described in following section.

2.1. Principle of BP neural network

The BP network structure is composed of one input layer, one output layer and several hidden layers. The number of hidden layers is selected according to the degree of complication for the system. The structure of BP neural network is shown in Fig. 1. Neurons in the hidden layer are nuclei to influence the training result. Determining the number of the neurons is the most important factor in hidden layer. The BP neural network has feed-forward stage and back-propagation stages. The parameters of feed-forward stage are defined as

$$m_g = f(w_g), \tag{1}$$

$$w_g = \sum_{f=1}^{3} U_{fg} l_f, \tag{2}$$

$$n_h = f(w_h), \tag{3}$$

$$w_h = \sum_{g=1}^{5} V_{gh} m_g, \tag{4}$$

$$f(x) = \frac{1}{1 + e^{-x}}, \tag{5}$$

where m_g and n_h are the neuron output of the hidden layer and the output layer, respectively. l_f is the input vector, w_g and w_h are the input of the gth neuron in the hidden layer and the hth neuron in the output layer, respectively. U_{fg} and V_{gh} are the weight values between the input layer and the hidden layer, the hidden layer and the output layer, respectively. $f(x)$ is activation function. After the feed-forward stage, the BP network can not arrive at the optimum target, which is to minimize error in this structure. So the weight values are adjusted to decrease the expected error by the back-propagation stage. The BP neural network is designed to minimize error function in the weight space. The minimum error used to train the network is as follows:

$$E = \frac{1}{2P} \sum_{1}^{h} \sum_{q=1}^{p} (n_{qh} - t_{qh})^2, \tag{6}$$

where n_{qh} is the corresponding actual output and p is the training sample number; t_{qh} is the hth component of the

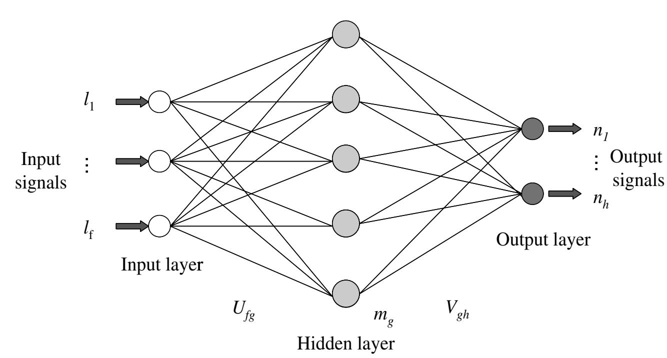

Fig. 1. Structure of BP neural network.

qth expected value. The weight values in back-propagation stage is defined as

$$U_{fg}(t+1) = U_{fg}(t) + \eta\delta_g l_f + \alpha[U_{fg}(t) - U_{fg}(t-1)], \quad (7)$$

$$V_{gh}(t+1) = V_{gh}(t) + \eta\delta_h m_g + \alpha[V_{gh}(t) - V_{gh}(t-1)]. \quad (8)$$

Here, η is the learning rate; α is the momentum coefficient; and δ_g and δ_h are learning signals as follows:

$$\delta_g = \sum_1^h V_{gh} f'(w_g), \quad (9)$$

$$\delta_h = (n_h - t_h) f'(w_h). \quad (10)$$

The network adjusts the weight value until the training result arrives at the convergence conditions. When the condition is convergent, the network finishes the procedure for the training module in the BP neural network.

2.2. Principle of RBF neural network

The RBF neural network is a feed-forward network with two layers and a structure is shown in Fig. 2. First, the input signals (x_i) are sent to a hidden layer that is composed of RBF neural units. The second layer is the output layer, and the transfer functions of the neurons are linear units. The transfer function of hidden layer is generally a non-linear Gaussian function which is shown in Fig. 3, and this equation is defined as

$$a_j = a(v_j) = \exp\left(-\frac{v_j^2}{2\sigma_j^2}\right), \quad (11)$$

where σ_j is a width of the jth neuron, v_j is presented by Euclidean norm of the distance between the input vector and the neuron center calculated as follows:

$$v_j(x) = \|x - c_j\| = \sqrt{\sum_{i=1}^{r}(x_i - c_{j,i})^2}, \quad i = 1, 2, \ldots, r, \quad (12)$$

where c_j is a center of the jth RBF unit.

The width of an RBF unit is selected as the root mean-square distance to the nearest jth RBF unit. For the jth unit, the width σ_j is defined as

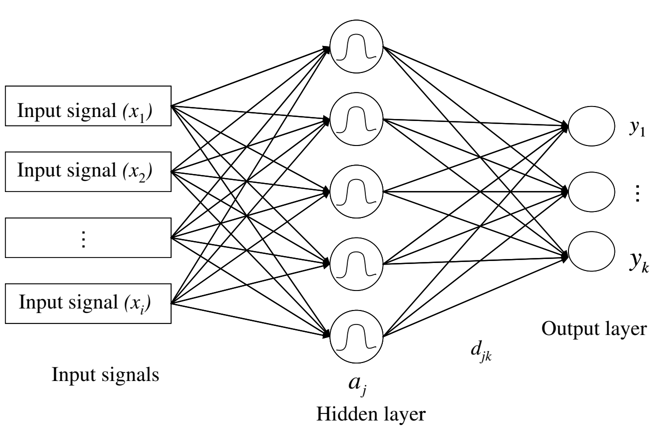

Fig. 2. Structure of RBF neural network.

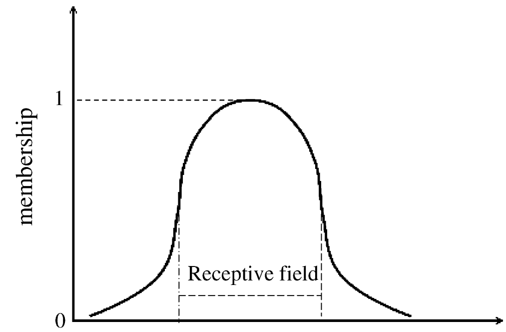

Fig. 3. Non-linear Gaussian transfer function.

$$\sigma_j = \left(\frac{1}{\varepsilon}\sum_{h=1}^{\varepsilon}\|c_j - c_h\|^2\right)^{1/2}, \quad (13)$$

where c_j is a center of the jth RBF unit, $c_1, c_2, \ldots, c_\varepsilon$ are the nearest unit centers to the unit j. And the output value is defined as

$$y_k = \sum_{j=1}^{s} d_{jk} a_j, \quad (14)$$

where y_k is the kth subsection of the y in the output layer, d_{jk} is the weight from the jth hidden layer neuron to the kth output layer neuron, and a_j is the output of the jth node in the hidden layer.

Training the RBF network involves determining the number of RBF units, the width of RBF units and the output layer weight values. The criterion is to minimize the sum of squared errors (SSE) defined as

$$\mathrm{SSE} = \frac{1}{2}\sum_{i=1}^{S}\sum_{k}\{t_k^i - y_k^i(X^i)\}^2, \quad (15)$$

where t_k^i are the expected values of the network output input vector X^i, and S is the number of training samples. The number of hidden RBF units is an important factor to determine the predictive properties of the network. The number of hidden units is calculated automatically until the expected SSE value in this research is found. The neural network uses various numbers of RBF units to evaluate the best predictive property. The hidden layer determines the number of RBF units and the width of RBF unit. After procedure of the hidden layer, the network has one weight value connected to the output layer. The output layer weight value is trained by linear squares regression.

3. Experimental investigation and Implementation of neural networks

3.1. Experimental arrangement of scooter platform

An experimental investigation is used to verify the proposed adaptive order tracking with neural networks for the fault diagnosis in scooter platform. Using the adaptive order tracking approach analyzes sound emission signal

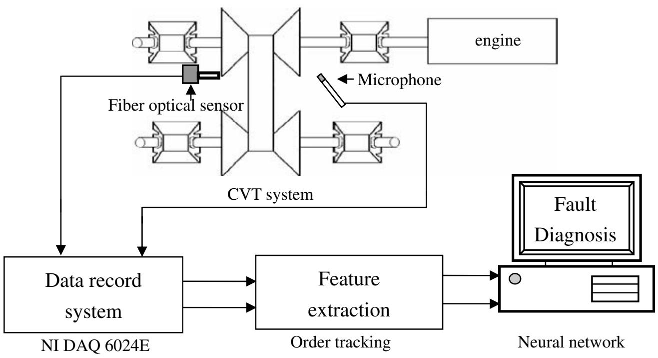

Fig. 4. Experimental arrangement and procedure of the scooter fault diagnosis system.

for extracting its order features, and neural networks utilize order features to classify fault clusters under various operating conditions. The experimental arrangement and procedure of the scooter fault diagnosis system are shown Fig. 4. In this experimental arrangement, a scooter platform with an electronic fuel injection system engine is used. A condenser microphone (PCB 130D20) is utilized to measure the sound emission of the scooter. A fiber optical sensor (PW-PH02) is employed to extract the crankshaft speed and angular displacement of the engine as reference inputs of the order tracking procedures in the diagnostic system. In this research, five engine operation conditions of the scooter are designed in the experimental procedure. These conditions include no fault in the platform, pulley damaged, belt damaged, air leakage of the intake manifold and clutch damaged. In the experimental work, the engine is operated in idling condition (1700 rpm), 2000 rpm, 2500 rpm, 3000 rpm, 3500 rpm and run-up test condition. The shaft speed of the engine in the run-up test condition is shown in Fig. 5.

3.2. Evaluation of neural networks in fault diagnosis system

After the measurement of the experimental work, the adaptive order tacking technique is used to establish the different order figures from the dynamic sound emission signals. The frequency normalized is defined as the sound emission features with various engine crankshaft speeds. The order amplitude figures under the idle condition without any fault in the scooter platform are shown in Fig. 6, which presents the first ten order amplitude figures. Then each order figure is converted into an averaged value. The averaged value of each order is defined as

$$K_u = \frac{\Sigma A_s}{N_t}, \tag{16}$$

where A_s is a point of every order amplitude, and N_t is the number of points in the order figures. The order figure is then converted into the order curve figure of average value, as shown in Fig. 7. The order curve figure is convenient to be a feature as input for neural networks in this diagnostic system.

After the procedure of extraction, the neural networks approach is used in the proposed scooter fault diagnosis. In the present study, both BP network and RBF network are evaluated for the proposed system, worked in both training module and testing module. The process of the proposed neural network is shown in Fig. 8. The neural networks use the knowledge base to train data and then utilize the testing engine to verify the experimental results. In the scooter experiment, 10 data sets are used to train various faults in neural network, and 40 testing data sets are used to verify the results of training under various engine operating conditions. The training module is the most important procedure in the neural network. The two networks have different training techniques and different structures for the training module, but they have the same testing module to verify the training results in the testing module.

The principle of BP neural network training has been introduced and the process of the training block diagram is shown in Fig. 9. First, the BP network decides the training structure, is composed of one input layer, one hidden layer and one output layer. Training of the BP network establishes some initial conditions, including the number of neurons, the convergence condition and the expectation output. In particular, determining the number of the neurons is the crucial factor for the hidden layer. If too many neurons are used, it is difficult for the network to converge and training time is increased. When using too few neurons, it leads to poor efficiency. Determining the number of neurons in the hidden layer according to human experience is necessary. After deciding the initial conditions, the

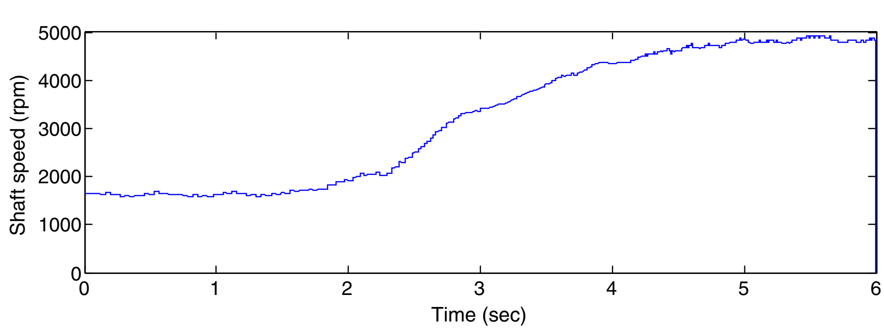

Fig. 5. Revolution of scooter in run-up test condition.

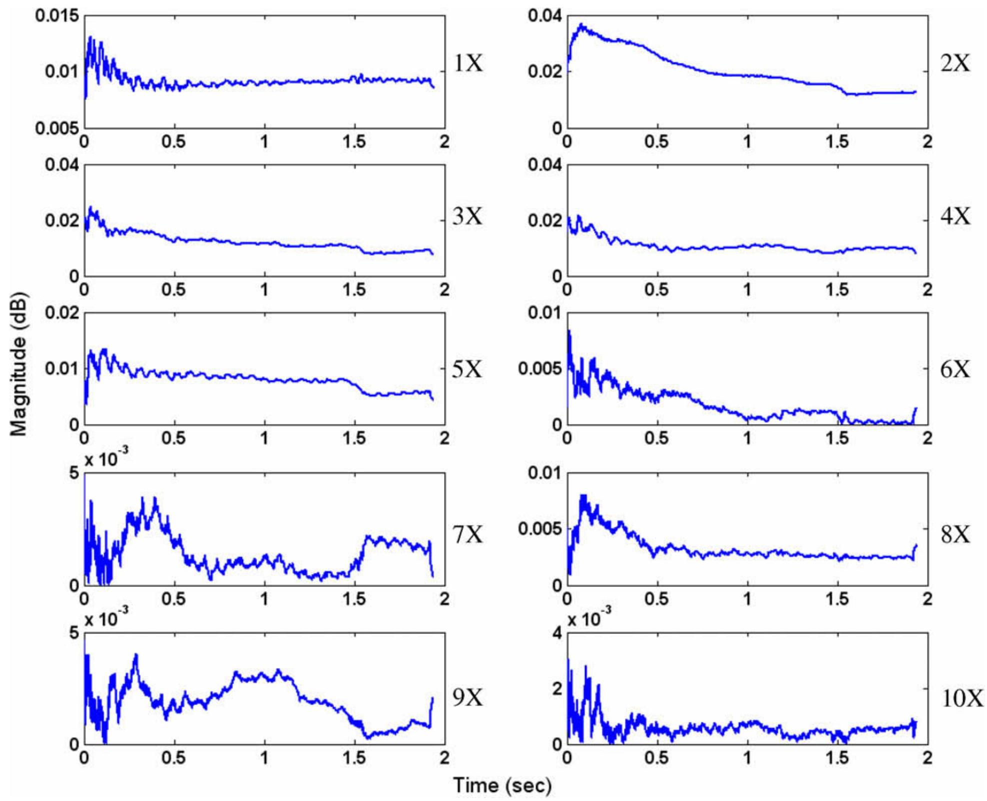

Fig. 6. Order figures displayed for engine at idle condition.

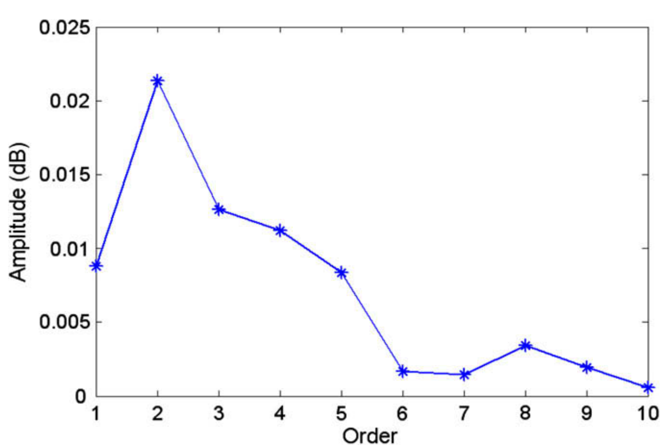

Fig. 7. Order curve figure displayed for engine speed at idle condition.

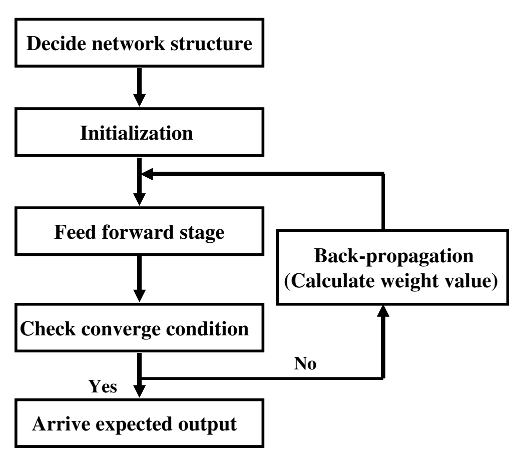

Fig. 9. Process of BP training block diagram.

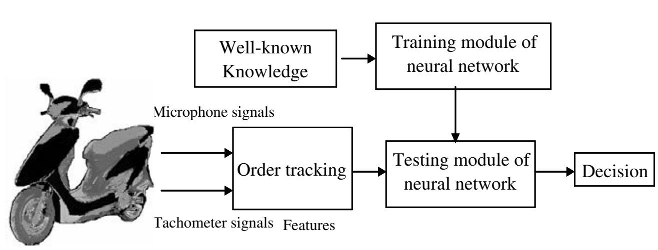

Fig. 8. Experimental procedure and neural network of the scooter fault diagnosis system.

feed-forward stage and back-propagation stage are used to adjust the weight values continuously until the result of training module arrives at the convergence condition and the expect output. If the result of training module can not converge, the initial conditions will be emended. When the condition is convergent, they finish the procedure of training module in the BP neural network.

Similar to the BP neural network, the RBF neural network is also used for the training structure, which involves in a hidden layer and an output layer. The training structure of the RBF network is simpler than BP network.

The feed-forward stage is used to calculate the result of output in the training RBF network. The hidden RBF unit is a key factor to decide the predictive properties of the network. The hidden layer is composed of the number of RBF units and the width of RBF units. The number of hidden units is calculated automatically, and the RBF units are increased one by one until the expected output is found. The width of each neuron can be determined for the suitable form. From the result of various numbers and width ones estimate the best predictive property in neural network. After the procedure for the hidden layer, the output layer weight value is trained by linear squares regression approach. This structure combines the result of the hidden layer and output layer to finish the training module in the RBF neural network. After the procedure for the training module, the testing engine is used to verity the training results in the neural networks. The results and discussion will be presented in following section

4. Results and discussion

The results of the proposed fault diagnosis system applied in a motor scooter platform under various operating condition with both BP and RBF neural networks is

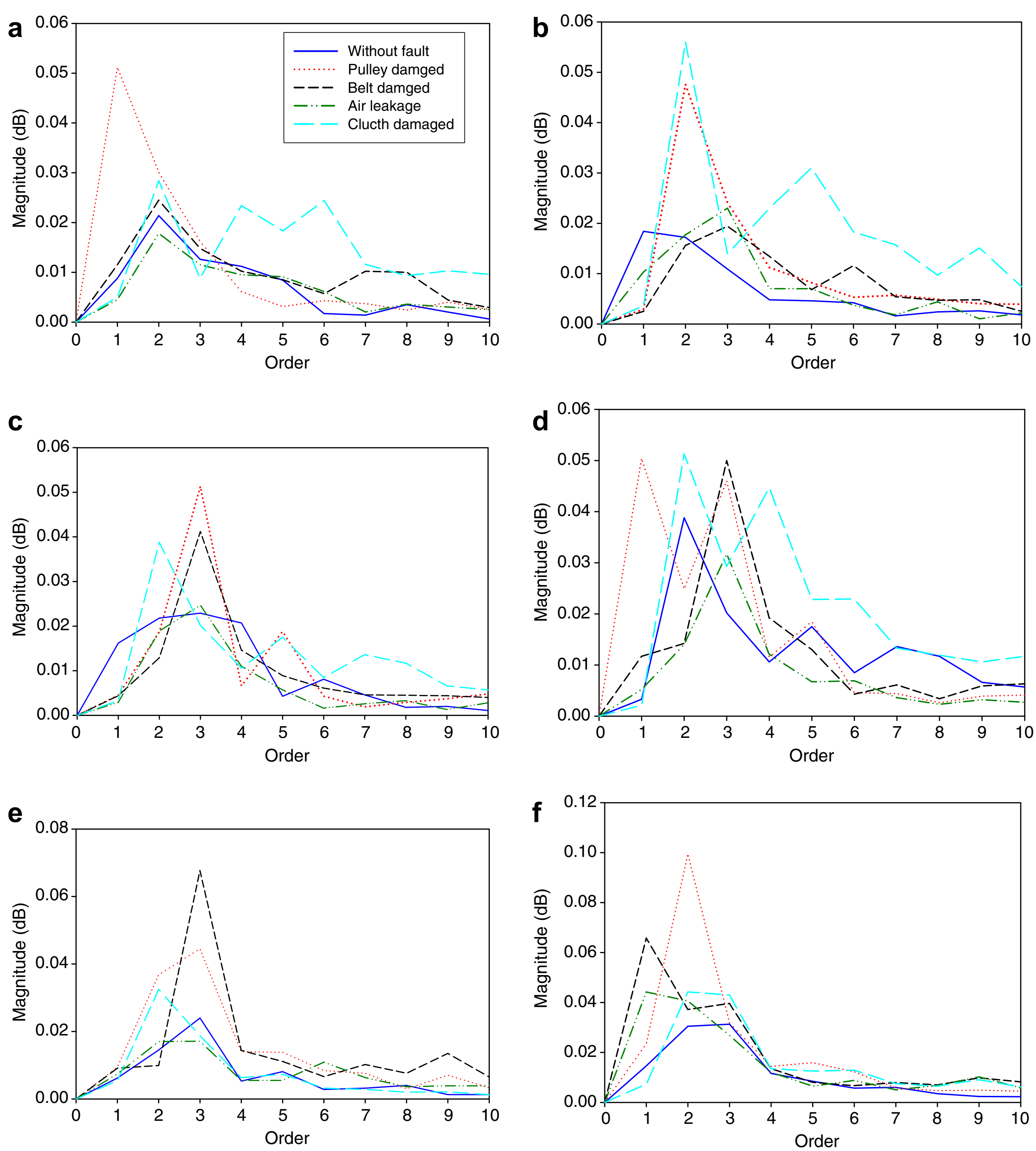

Fig. 10. Order curve figures at various engine conditions. (a) idle condition; (b) 2000 rpm; (c) 2500 rpm; (d) 3000 rpm; (e) 3500 rpm; (f) run-up test.

presented in this section. Firstly, the order amplitude figures have been established, and the order figures are transferred to order curve features as input in the neural network of fault diagnosis system. However, the different faults occur with different properties of the order curve figure in the mechanical system. The order curve figures of order tracking in various conditions are summarized in Fig. 10. By observing the figures for normal conditions, pulley damaged, belt damaged, intake air leakage and clutch damaged conditions under various engine operating conditions are indicated by the different lines.

The results of fault classification under various engine operating conditions using the BP and RBF neural networks are summarized in Tables 1 and 2. The results of BP and RBF neural network have an acceptable recognition rate for fault classification in various fault conditions. In particular, the results of RBF neural network are more efficient than the BP neural network for classifying fault clusters in this system, and the best recognition rate of RBF neural reaches 100% under several engine operating conditions. Meanwhile, the initial condition of RBF neural network only defines expected output, and the number of hidden units is calculated automatically and trained to expected target more conveniently. However, the initial conditions of the BP neural network include the number of neurons, the convergence conditions and the expected output. In particular, determining the number of neurons by a trial and error approach will take too much time and present difficulty for the optimal training target. The BP neural network has feed-forward stage and back-propagation stage, while the RBF only has a feed-forward stage. The RBF neural network has a simple structure for the training module, and there are fewer calculations than the BP neural network. So the RBF neural network needs less associative memory, although the learning speed and the convergence rate are very rapid. The characteristic comparison between BP and RBF neural networks in this fault diagnosis system are summarized in Table 3. According to the summation of the above advantages and experimental results, the RBF neural network is more efficient than the BP neural network for fault diagnosis although the BP neural network can find the optimal final parameters for training module and presents an acceptable recognition rate.

Table 1
Results of fault diagnosis system using BP neural network at various fault conditions

Engine operation	Recognition rate of fault condition (%)				
	Without fault	Pulley damaged	Belt damaged	Air leakage	Clutch damaged
Idle	100	97.5	92.5	100	100
2000 rpm	100	95	92.5	100	100
2500 rpm	100	97.5	92.5	100	97.5
3000 rpm	100	100	100	100	100
3500 rpm	97.5	90	97.5	97.5	85
Run-up	100	90	85	100	87.5

Table 2
Results of fault diagnosis system using RBF neural network at various fault conditions

Engine operation	Recognition rate of fault condition (%)				
	Without fault	Pulley damaged	Belt damaged	Air leakage	Clutch damaged
Idle	100	97.5	100	100	100
2000 rpm	100	100	100	100	100
2500 rpm	100	100	100	100	100
3000 rpm	100	100	100	100	100
3500 rpm	100	100	97.5	100	95
Run-up	100	97.5	87.5	100	100

Table 3
Characteristic comparison between BP and RBF neural networks in fault diagnosis system

Characteristics	Neural network	
	BP	RBF
Structure	Complex	Simple
Initial conditions	Some	One
Training type	Feed-forward stage, back-propagation stage	Feed-forward stage
Calculation quantity	Large	less
Determining number of neurons	Trial and error	Automatic
Convergence speed (Training time)	Tardy (long)	Rapid (short)
Recognition rate	Acceptable	Excellent

5. Conclusions

The present study describes a fault diagnosis system using acoustic emission signals with an adaptive order tracking technique and neural networks for a scooter platform. The adaptive order tracking extracts the order features as input for a neural network in the proposed fault diagnosis system. The neural networks have property of self-learning to cluster together for the same order features. This intelligent system establishes the training module and testing module. The experimental results indicate that the proposed system has great probability for accuracy in fault diagnosis under various operation conditions.

Acknowledgement

The study was supported by the National Science Council of Taiwan, the Republic of China, under Project Number NSC-95-2622-E-018-001-CC3.

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