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Development of an expert system for fault diagnosis in scooter engine platform using fuzzy-logic inference

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Abstract

In the present study, a fault diagnosis system using acoustic emission with an adaptive order tracking technique and fuzzy-logic interference for a scooter platform is described. Order tracking of acoustic or vibration signal is a well-known technique that can be used for fault diagnosis of rotating machinery. Unfortunately, most of the conventional order-tracking methods are primarily based on Fourier analysis with the revolution of the machinery. Thus, the frequency smearing effect often arises in some critical conditions. In the present study, the order tracking problem is treated as the tracking of frequency-varying bandpass signals and the order amplitudes can be calculated with high resolution. The order amplitude figures are then used for creating the data bank in the proposed intelligent fault diagnosis system. A fuzzy-logic inference is proposed to develop the diagnostic rules of the data base in the present fault diagnosis system. The experimental works are carried to evaluate the effect of the proposed system for fault diagnosis in a scooter platform under various operation conditions. The experimental results indicated that the proposed expert system is effective for increasing accuracy in fault diagnosis of scooters.

Keywords: Fault diagnosis; Fuzzy logic inference; Adaptive order tracking; Acoustic emission

1. Introduction

The technique of early fault diagnosis is used to prevent serious damages in a mechanical system. Rotating machinery such as internal combustion engines, cooling fans and air compressors can have their vibration and acoustic emission signals monitored for early fault diagnosis. Conventional fault diagnosis using vibration and acoustic emission signals already exists in the form of techniques for applying the time and frequency domain of signals, and analyzing the amplitude difference in signals (Peng & Chu, 2004; Zheng, Li, & Chen, 2002). However, the conventional methods are not always effective for application under certain critical conditions such as using a fixed sampling frequency for fast Fourier transform (FFT) analysis in rapid fluctuation of the machinery speed. Order tracking is a well-known technique that can be used for fault diagnosis of rotating machinery. Conventional order tracking technology is based on the frequency analysis, where narrow band spectra of the frequency-varying signals utilize proper time-windowing, unfortunately, the smearing problem that include spaced orders and crossing orders often arise critical conditions (Vold & Leuridan, 1993). In order to overcome this problem, a number of new techniques have been proposed, e.g. adaptive order tracking techniques (Bai, Huang, Hong, & Su, 2005; Bai, Jeng, & Chen, 2002), and adaptive wavelet analysis techniques (Lin & Zuo, 2003; Tse, Yang, & Tam, 2004). Most of the methods can extract the order of features embedded in the vibration and acoustic emission signals.

In the present study, a high resolution adaptive order tracking technique is used to create different order amplitude figures of the scooter platform under various engine

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operation conditions as the data bank for the fault diagnosis expert system (Wu, Huang, & Huang, 2004; Wu, Huang, & Chen, 2005). In the proposed technique, a more accurate description of signal feature can be drawn by converting frequency spectra into order spectra, and order is defined as the frequency normalized with various shaft speeds. The technique focuses on adaptive filter based on the Kalman filter. The continuous acoustic emission signal is measured and analyzed using adaptive Kalman filtering order tracking that can eliminate noise and reconstruct the acoustic emission signal in this system. High resolution adaptive order tracking is also used to practically analyze and track the energy of order signal from the dynamic signal. Meanwhile, the order tracking is formulated in terms of state space models. The multiple harmonics of acoustic emission signals have been used as different order amplitude figures of the scooter in this system. The amplitudes of different order can be calculated for extracting the feature of the order figures. After processing signal analysis that obtained order features, the fuzzy-logic inference is used to classify the faults automatically. Many machinery fault diagnostic approaches use automatic diagnosis in

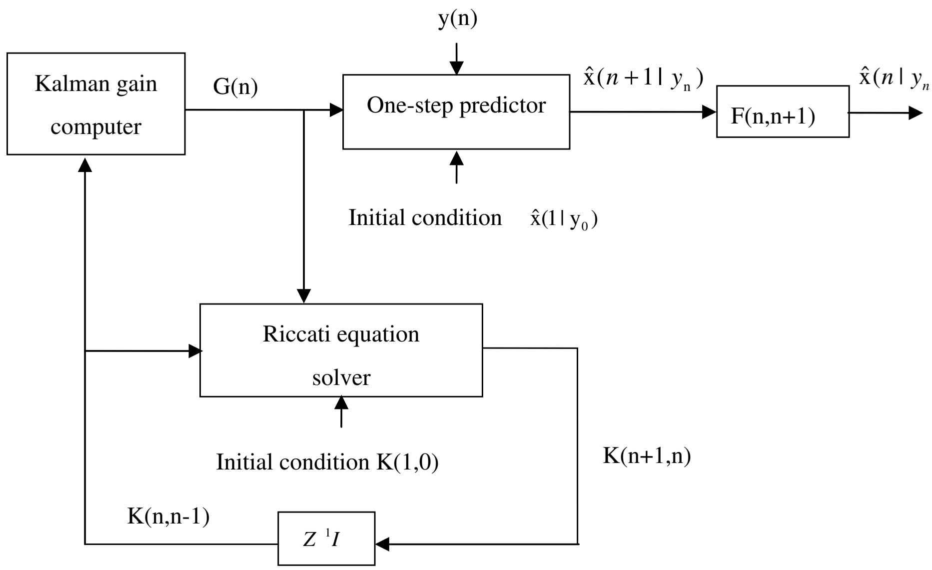

Fig. 1. Block diagram of adaptive Kalman filter.

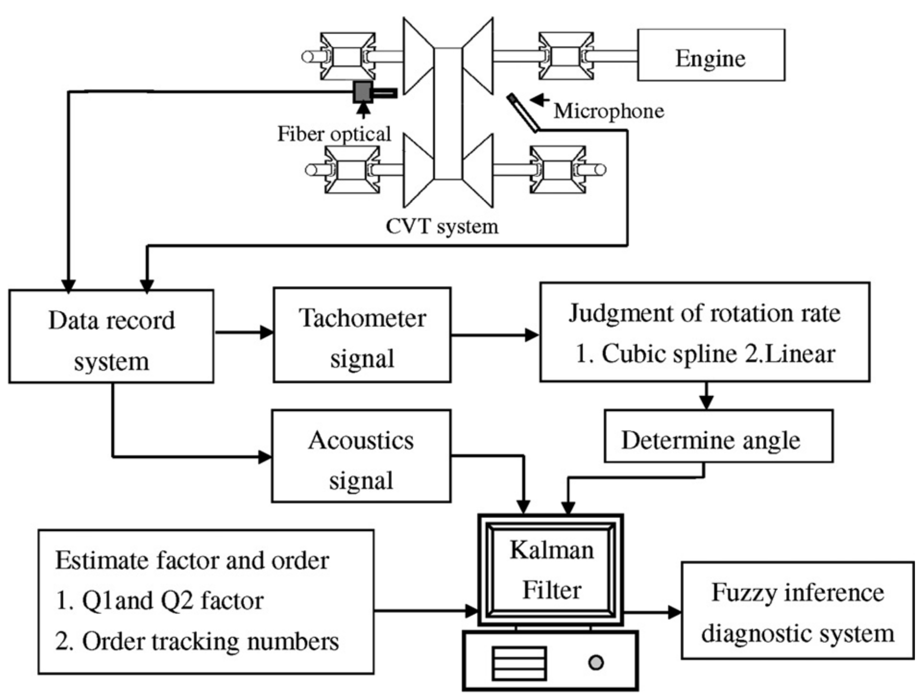

Fig. 2. Signal-flow graph representation of adaptive order tracking.

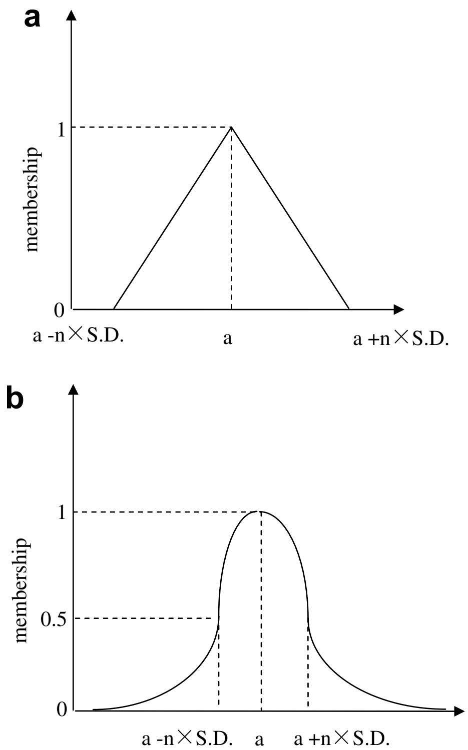

Fig. 3. Membership function: (a) triangular membership function and (b) π membership function.

order to increase accuracy caused by subjective human determination. Fuzzy logic is a powerful tool for complex numerical analysis and knowledge modeling. (Huang, Yang, & Huang, 1997) proposed a fuzzy logic system for the fault diagnosis system. (Mechefske, 1998) also proposed a fuzzy logic inference for fault classification by machinery vibration signal.

In the present study, a fuzzy-logic inference is proposed to develop the diagnostic rules of the data base in an order tracking amplitude features. The fuzzy logic inference can calculate complex numerical analysis and use a membership value easily explained by human. The membership function establishes the inference rules and the knowledge base to systematize the post-processing procedure in this system. Both the π and the triangular membership function will be compared for fault diagnosis by using order amplitude figures of the scooter with normal and four fault conditions. The structure and principle of high resolution adaptive order tracking technique and fuzzy logic inference are described in the following sections.

2. Principle of adaptive order tracking technique

In this section, an adaptive order tracking technique based on the Kalman filtering algorithm is described (Haykin, 1996). The analysis of the order tracking with the acoustic emission signal and shaft speed can be described as the amplitude of the frequency-modulated (Bai et al., 2002; Bai et al., 2005). The acoustic emission signal $x(t)$ of the rotating machinery containing k orders is usually represented as

Table 1
Rules of fuzzy logic inference for the fault diagnosis system

If					Then				
1X	2X	···	7X	8X	Normal	Fault 1	Fault 2	Fault 3	Fault 4
Low 1	Low 2	···	Low 1	Low 1	•				
Low 1	High 3	···	Low 2	Low 2		•			
High 2	High 1	···	Low 2	Low 1			•		
Low 3	High 2	···	Low 2	Low 1				•	
High 2	High 1	···	Low 1	Low 1					•

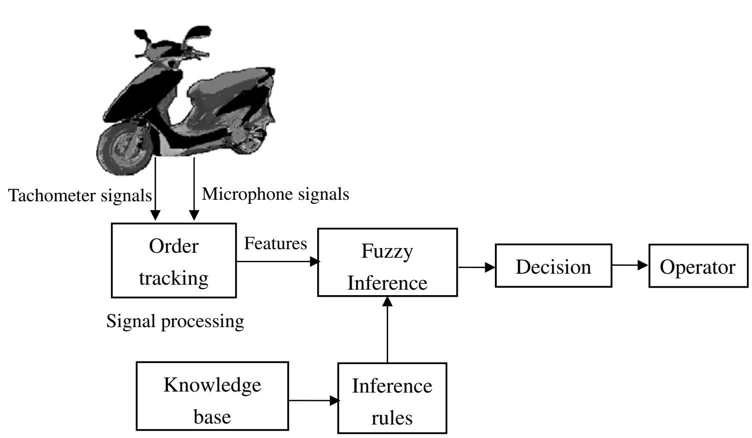

Fig. 4. Experimental arrangement and fault diagnosis system.

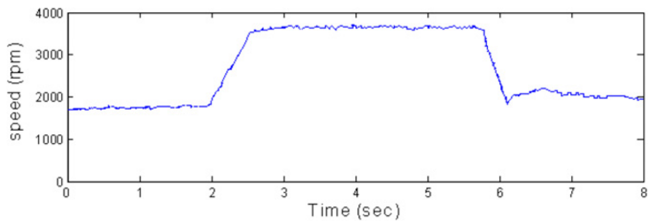

Fig. 5. Revolution of scooter in run-up test condition.

$$x(t) = A_1\cos[\theta(t)+\phi_1] + A_2\cos[2\theta(t)+\phi_2] + \cdots\cdots + A_k\cos[k\theta(t)+\phi_k]. \quad (1)$$

Eq. (1) can be expanded as

$$x(t) = A_{1I}\cos[\theta(t)] - A_{1Q}\sin[\theta(t)] + \cdots + A_{kI}\cos[k\theta(t)] - A_{kQ}\sin[k\theta(t)]. \quad (2)$$

By discrete time sampling, Eq. (2) can be represented as

$$x(n) = [\cos[\theta(n)] - \sin[\theta(n)] \cdots \cos[k\theta(n)] - \sin[k\theta(n)]]\begin{bmatrix} A_{1I} \\ A_{1Q} \\ \vdots \\ A_{kI} \\ A_{kQ} \end{bmatrix}. \quad (3)$$

The high-resolution order tracking based on Kalman filter has two equations. The first equation is called the process equation:

$$x(n+1) = F(n+1,n)x(n) + v_1(n). \quad (4)$$

Table 2
Membership value of consequence with π membership function at idle condition with pulley damaged

Faults	n (multiples of S.D.)				
	1	2	3	4	5
Normal	0.0030	0.0116	0.0243	0.0396	0.0562
Pulley	**0.5665**	**0.8202**	**0.9078**	**0.9451**	**0.9639**
Belt	0.0853	0.1826	0.2572	0.3187	0.3712
Air	0.0892	0.1185	0.1316	0.1430	0.1552
Clutch	0.0250	0.0780	0.1309	0.1752	0.2115

Table 3
True membership values in the fault diagnosis system

Test faults	The result of faults				
	Normal	Pulley	Belt	Air	Clutch
Normal	**1**	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	0	**1**	0	0	0
Pulley	0	**1**	0	0	0
	0	**1**	0	0	0
	0	0	**1**	0	0
Belt	0	0	**1**	0	0
	0	0	**1**	0	0
	0	0	0	**1**	0
Air	0	0	0	**1**	0
	0	0	0	**1**	0
	0	0	0	0	**1**
Clutch	0	0	0	0	**1**
	0	0	0	0	**1**

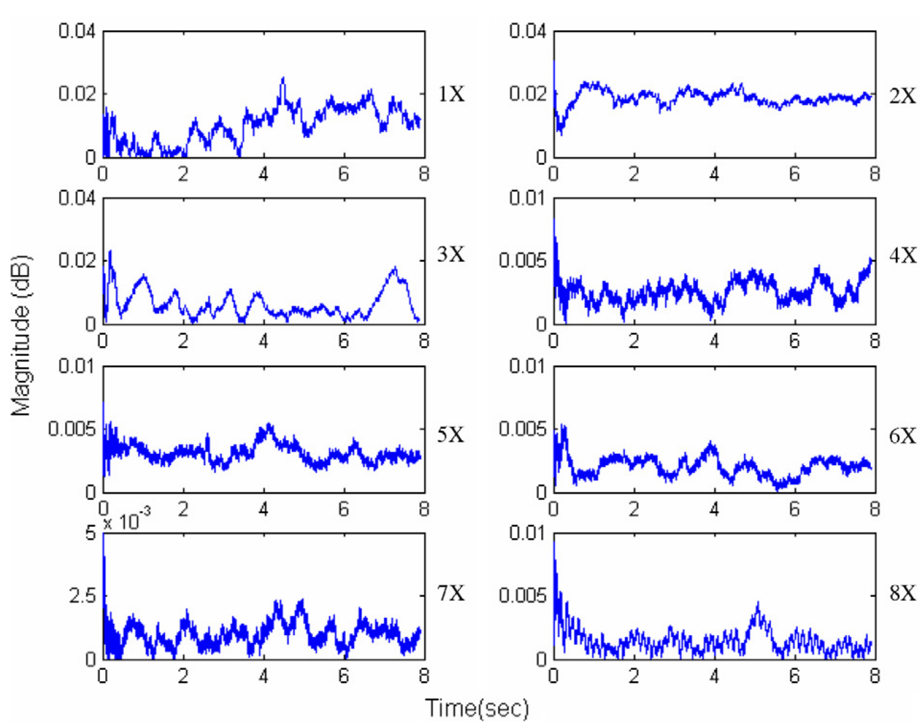

Fig. 6. Order figures displayed for engine speed at idle condition.

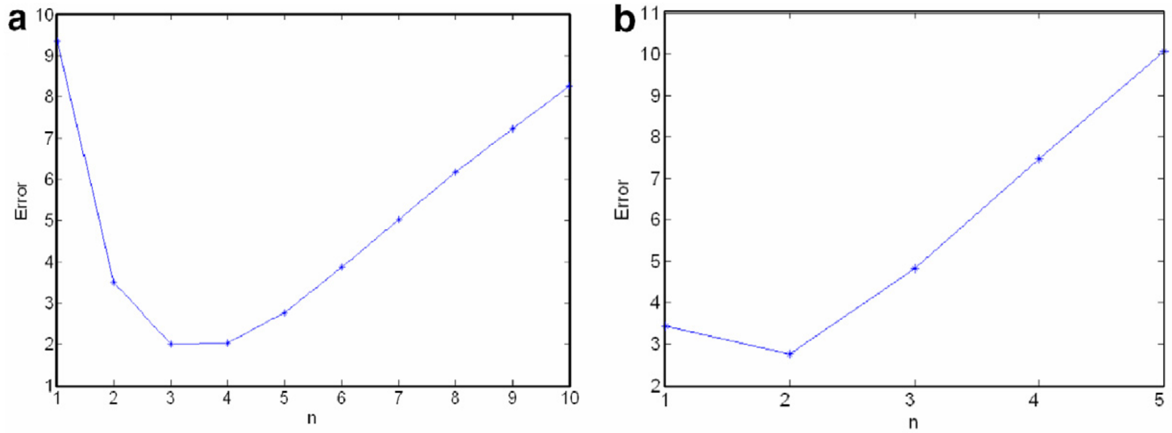

Fig. 7. Performance of membership function versus the parameter n at idle condition: (a) triangular membership function and (b) π membership function.

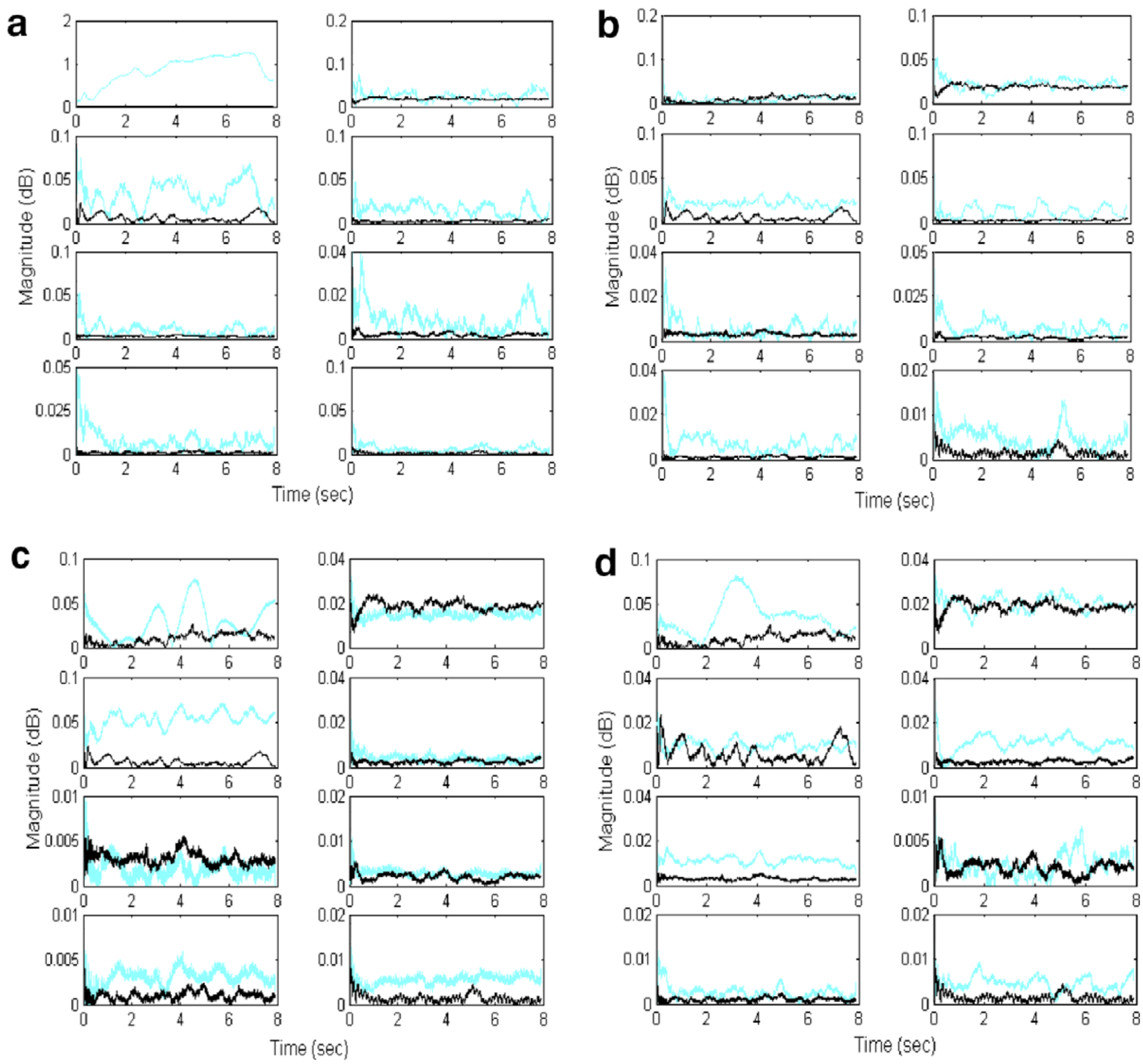

Fig. 8. Order amplitude figures of scooter acoustic emission in idle condition. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

Meanwhile, the second equation is called the measurement equation:

$$y(n) = C(n)x(n) + v_2(n) \tag{5}$$

The vectors $v_1(n)$ and $v_2(n)$ represent zero-mean and white noise. The noise vectors $v_1(n)$ and $v_2(n)$ are individually independent and $E[v_1(n)v_2^H(k)] = 0$ for all n and k.

The wave of the amplitude-modulated signal can track its frequency continually with respect to the fundamental and multiple frequencies in the rotating machinery. Using this form, the Kalman filtering algorithm is recommended to structure this model by the process and measurement equations.

Measurement equation:

$$y(n) - \sum_{i=-N}^{N} A_i(n)\exp[\mathrm{j}\theta_i(n)] = v_2(n). \tag{6}$$

Process equation:

$$\nabla^2 A_i(n) = v_1(n). \tag{7}$$

In common usage, $A_i(n)$ can be assumed by the autoregressive (AR) model.

$$H(z)A_i(z) = V_1(z). \tag{8}$$

The state transition matrix and measurement matrix are described as

$$\mathbf{F}(n+1,n) = \begin{bmatrix} \mathbf{P} & \mathbf{0} & & \cdots & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{P} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \cdots & & \mathbf{0} & \mathbf{P} \end{bmatrix}, \tag{9}$$

$$\mathbf{C}(n) = [\exp[\mathrm{j}\theta_k(n)] \;\; 0 \;\; \cdots \;\; \exp[\mathrm{j}\theta_0(n)] \;\; 0 \;\; \cdots \;\; \exp[\mathrm{j}\theta_{-k}(n)] \;\; 0]. \tag{10}$$

The Kalman filtering procedure can be summarized as follows:

$$\mathbf{G}(n) = \mathbf{F}(n+1,n)\mathbf{K}(n,n-1)\mathbf{C}^H(n) \times [\mathbf{C}(n)\mathbf{K}(n,n-1)\mathbf{C}^H(n) + Q_2(n)]^{-1}, \tag{11}$$

$$\alpha(n) = y(n) - \mathbf{C}(n)\hat{\mathbf{x}}(n|y_{n-1}), \tag{12}$$

$$\hat{\mathbf{x}}(n+1|y_n) = \mathbf{F}(n+1,n)\hat{\mathbf{x}}(n|y_{n-1}) + \mathbf{G}(n)\alpha(n), \tag{13}$$

$$\mathbf{K}(n+1,n) = \mathbf{F}(n+1,n)\mathbf{K}(n)\mathbf{F}^H(n+1,n) + Q_1(n). \tag{14}$$

The representation of a block diagram in the Kalman filter is depicted in Fig. 1. The signal-flow graph of adaptive order tracking and the identification of parameters by adaptive order tracking are represented in Fig. 2. By

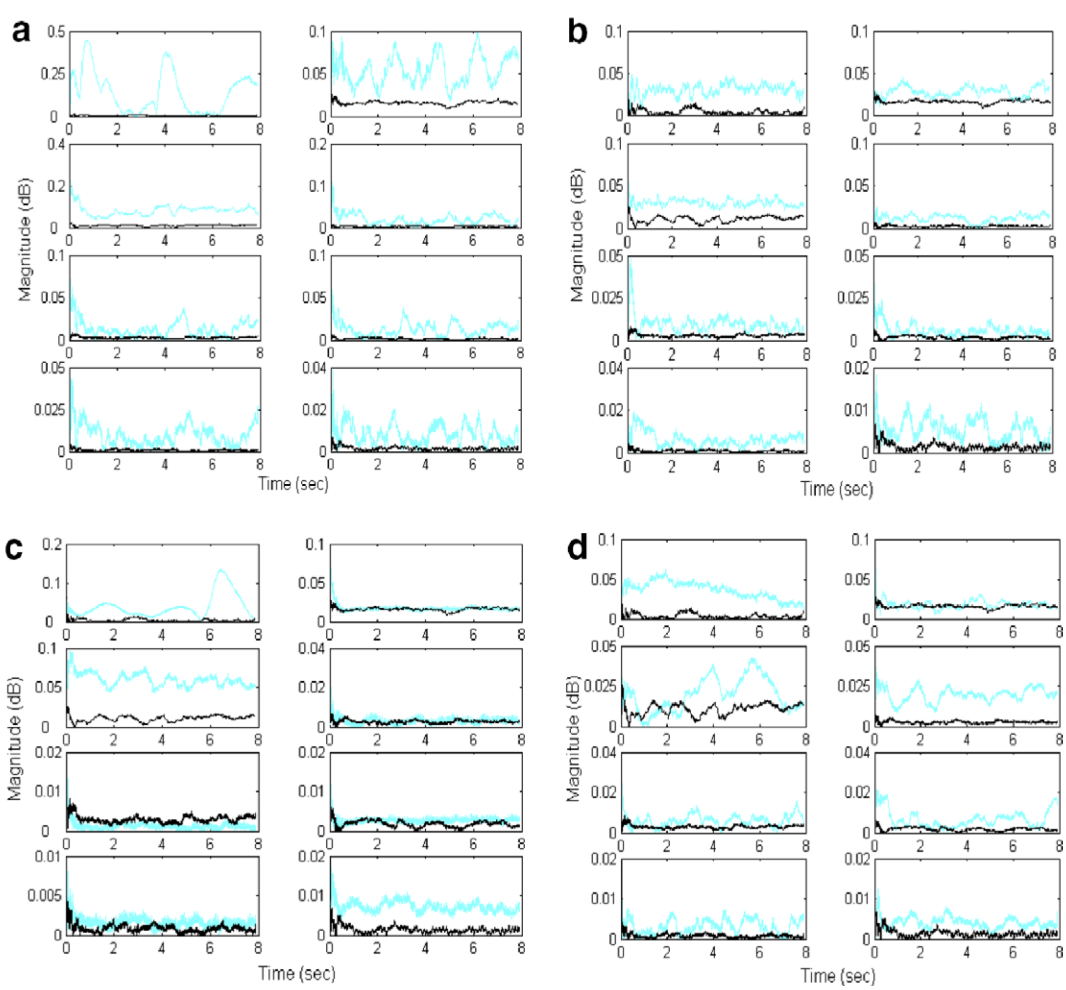

Fig. 9. Order amplitude figures of scooter acoustic emission in 2000 rpm. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

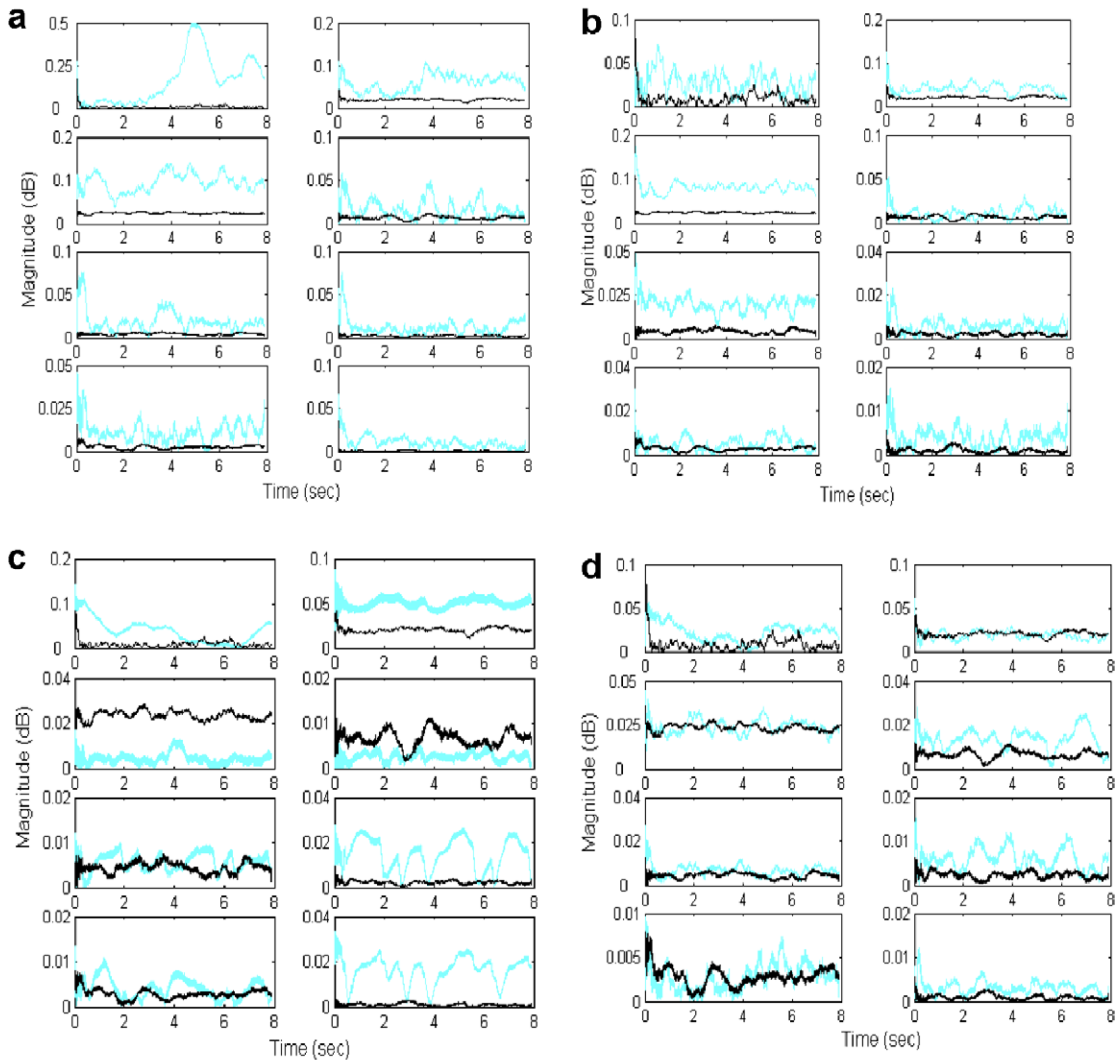

Fig. 10. Order amplitude figures of scooter acoustic emission in 2500 rpm. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

adding the Kalman filtering algorithm we can eliminate noise and reconstruct the sound signals in this system. This proposed adaptive algorithm could increase the accuracy of the order amplitude figures and conveniently extract the features.

3. Fuzzy logic inference for fault diagnosis

Fuzzy logic is a useful approach to simplify a complex system in engineering application. In the present study, a fuzzy-logic inference is used to calculate complex numerical analysis with a membership value easily interpreted by humans (Awad & Wafik, 1999). After extracting the features of the proposed adaptive order tracking amplitude figures, fuzzy logic is used to automatically diagnose the faults in the designed scooter experimental platform. The fuzzy-logic inference is proposed to establish the diagnostic rules of the data bank in this fault diagnosis system. The amplitudes of different order can be calculated for extracting the features of the order figures. The energy of order figure amplitude is calculated by using root-mean-square (rms) as the input values:

$$W = \sqrt{\frac{1}{H}\left(\sum_{h=1}^{H} Y(h)\right)} \tag{15}$$

where W is the rms value of order amplitude, Y is an order amplitude, and H is the number of the order amplitude. After obtaining the order feature of the order figures, the data analysis includes finding the mean value and standard deviation of each order after the extracting feature procedure has finished. The decision of the membership function is also a key point and especially punctilious for fuzzy-logic inference. The fuzzy membership function has represented variable sets that include S, π, triangular and gauss. In the present study, the triangular and π membership function will be used to develop the fuzzy logic inference (Mechefske, 1998). The triangular and π membership functions are established as shown in Fig. 3. The equation of π membership function can be described as

$$\pi(z,a,b) = \frac{1}{1+\left(\frac{z-a}{b}\right)^2}, \tag{16}$$

where a is the mean value of each order, b is the n times the standard deviation (S.D.) in each order. The membership function establishes the inference rules and the knowledge base under fault decision conditions. The rules of fuzzy logic inference are defined as $\pm n$ times the standard deviation of each condition at each order. Those are used for the higher and lower limits of the fuzzy logic membership domain. The rules have been defined an inference rule variable x in universe of the discourse, and the equation follows as:

$$(A_1 \cap A_2 \cap \cdots \cap A_n)(x) = \min\{A_1(x), A_2(x)...A_n(x)\}, \quad \text{for all } x \in X, \tag{17}$$

where $A(x)$ is a rule of the membership function. Eq. (17) can be represented the Table 1. The processing procedure must be systematized with the inference rules in this system. The fuzzy membership domain is defined with various strength ranges from 0 to 1. The condition of maximal probability will be inferred according to the knowledge base and evaluation of the inference rules. The fuzzy logic inference could increase the efficiency of diagnosing faults in the present system.

4. Experimental investigation of fault diagnosis system

In the experimental investigation, the scooter acoustic emission signals were analyzed to verify the proposed fuzzy logic inference fault diagnosis system. The fault diagnosis system consists of the signal analysis and the fault inference. In the signal analysis, the adaptive order tracking with Kalman filter for extracting the order feature of acoustic emission signal is used, and fault inference utilizes a fuzzy logic approach to classify faults under different operating conditions. Experimental arrangement and the fuzzy logic system of the scooter defect diagnosis system

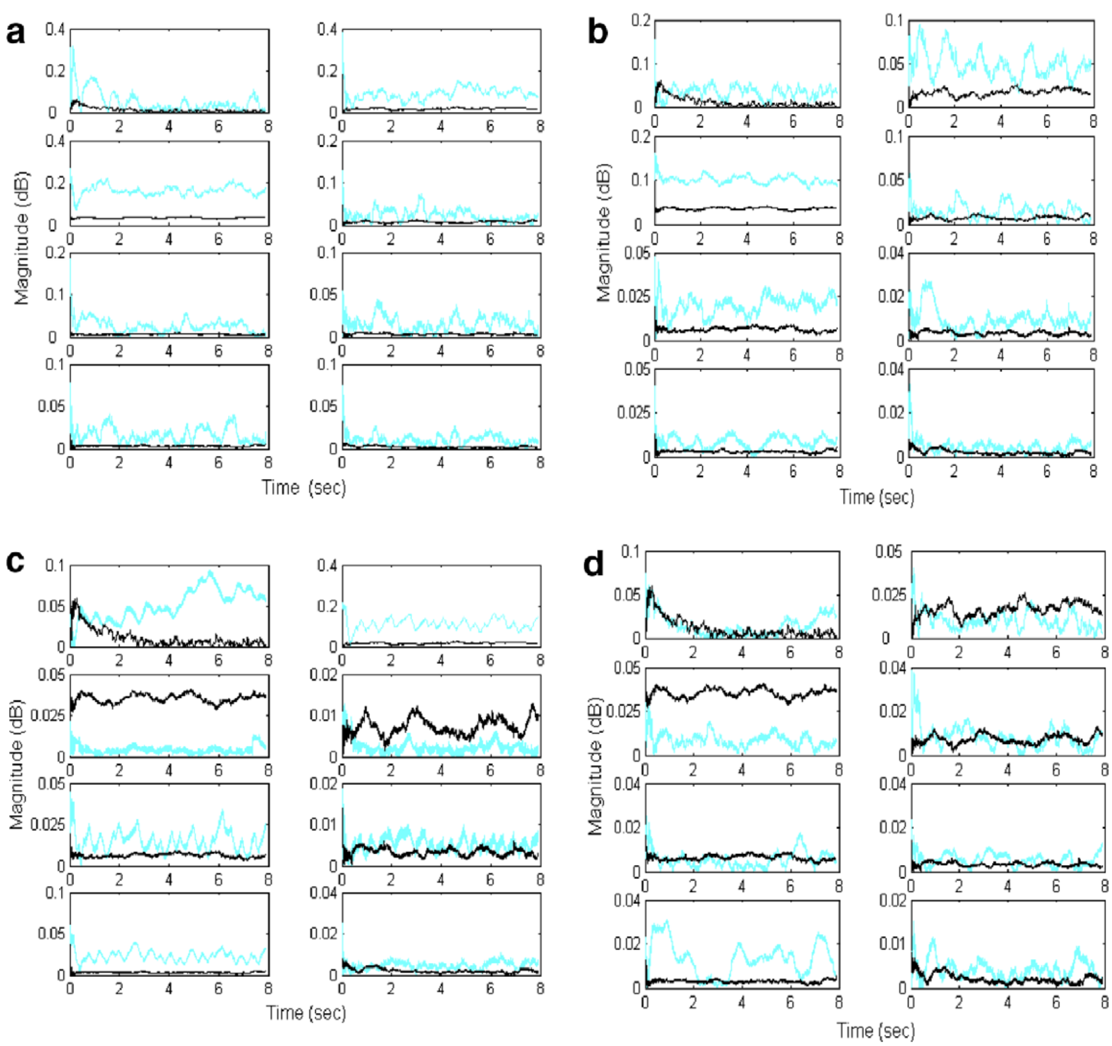

Fig. 11. Order amplitude figures of scooter acoustic emission in 3000 rpm. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

is shown Fig. 4. A scooter with an electronic fuel injection system, single-cylinder, four-stroke, 0.125-l internal combustion engine is used in this application. The sound emission signal is measured using a condenser microphone (PCB 130D20) located close to the scooter engine transmission. A fiber optical sensor (PW-PH02) is utilized to detect the revolution signal and angular displacement of the engine as reference signals of the order tracking procedures in the diagnostic system. The sampling frequency is chosen to be 20 kHz with the data record system (Hardware: NI 6024E; Software: Lab-view).

In the present study, five conditions of the scooter are used in the experimental work. These include without fault, pulley damage, belt damage, air leakage of the intake manifold and clutch damage. In the experimental work, there are 10 pieces of data in each fault condition to establish the fuzzy-logic inference. The engine is operated in an idling condition (1700 rpm), 2000 rpm, 2500 rpm, 3000 rpm, 3500 rpm and run-up test conditions. The engine revolution of the run-up condition is shown as Fig. 5. In particular, the run-up test is emphasized in this research because the adaptive order tracking can accurately track the energy of the order signal from the dynamic signal. After recording the signals, they would be used in order tracking analysis to track the energy of the order amplitude signal. Acoustic emission signal features could be drawn by converting the frequency spectrum into order spectrum, and order is defined as the frequency normalized with various shaft speeds. The first eight orders of the amplitude figures with adaptive Kalman filter under the idle condition without any fault in the scooter platform are shown as Fig. 6. The amplitudes of the order figures can be calculated for the feature as input for fuzzy logic inference.

After extracting the features, the fuzzy logic inference approach is used in the proposed fault diagnosis. First, the mean and the standard deviation of each condition at each order are estimated, and the higher and lower limits of the fuzzy logic membership domain as the fuzzy inference rules are defined. There are eight orders in one fault condition which means there are eight inference rules in

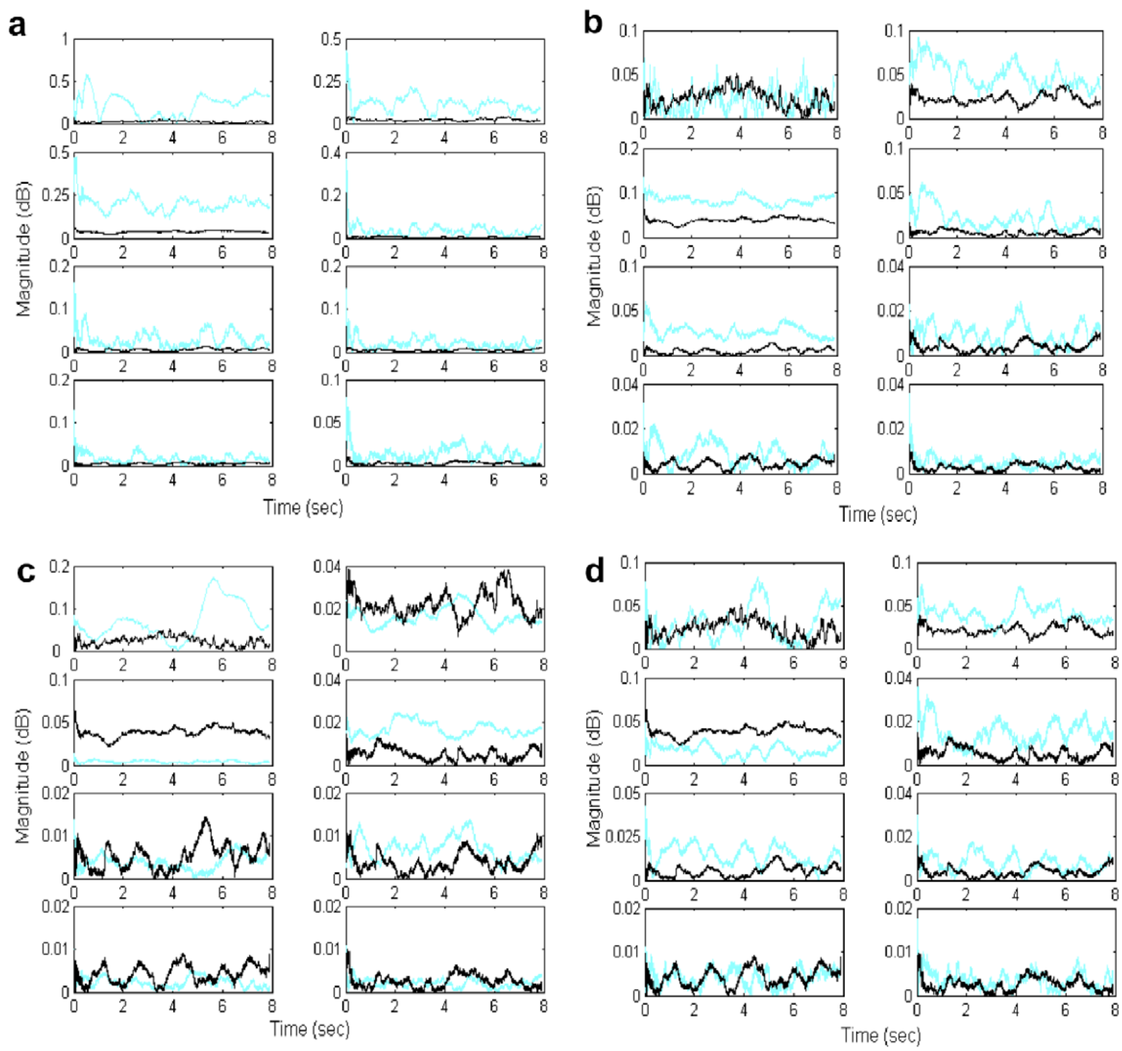

Fig. 12. Order amplitude figures of scooter acoustic emission in 3500 rpm. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

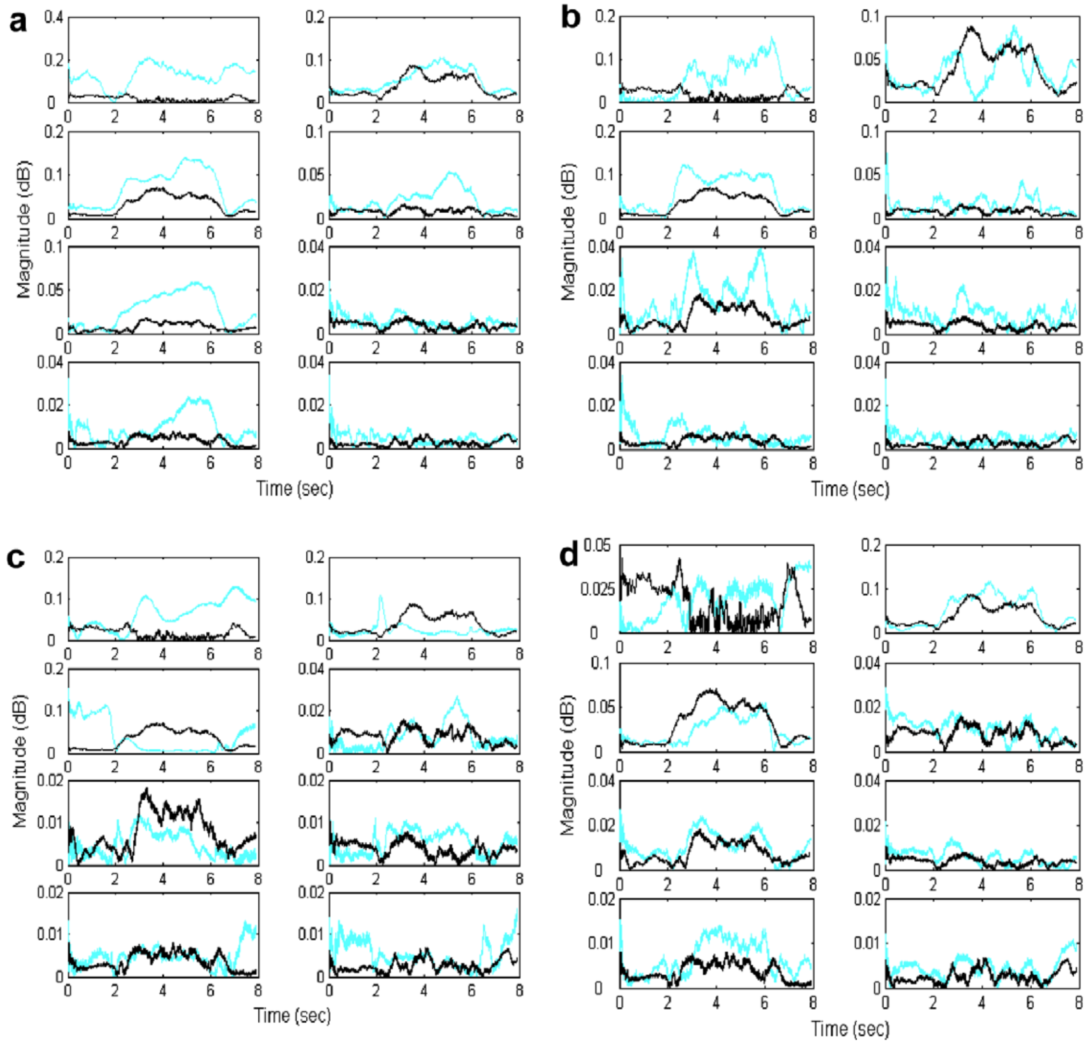

Fig. 13. Order amplitude figures of scooter acoustic emission in run-up condition. A solid line depicts scooter without any fault; a dashed line depicts scooter with various faults: (a) pulley damaged, (b) belt damaged, (c) air leakage of intake and (d) clutch damaged.

the system. After calculation by the inference rules and knowledge base, the results have been represented by membership values. The membership value of the fault diagnosis system is between 0 and 1, where 0 means impossible and 1 means possible. When the membership value is close to 1, this means the condition is true. The inference rules and knowledge base have been established based on the membership function. In this research, the triangular and π membership functions are proposed to develop the fuzzy-logic inference. The triangular membership function applies when tolerance of fault is large and the π membership function is applied in critical conditions.

Besides the membership function, choosing the optimum inference error versus n value could also increase the resolution of system. With fuzzy logic inference, the membership value of consequence with π membership function in the idling condition with pulley damage are calculated and summarized in Table 2. When the n is larger the membership domain is wider. The membership value of the accurate classification increases with an increasing n value. Nevertheless, the membership value of fault classification also increases with an increasing n value. Defining optimum inference error versus n value is necessary. The optimum inference error versus n value is determined by:

Table 4
The optimum n values with two different membership function under various operation conditions

n Value	Engine operation conditions					
Membership function	Idle	2000 rpm	2500 rpm	3000 rpm	3500 rpm	Run-up
Triangular	4	3	3	4	4	2
π	2	2	2	2	2	1

Table 5
Faults classification under various engine operation conditions with triangular membership function

Engine operation	Test faults	Membership value of faults				
		Normal	Pulley	Belt	Air	Clutch
Idle	Normal	**0.7746**	0.0413	0.1220	0.1953	0.0598
	Pulley	0	**0.7709**	0.1412	0.1047	0.0462
	Belt	0.1315	0.3227	**0.8087**	0.0929	0.1845
	Air	0.1163	0.1629	0.0494	**0.8626**	0.1210
	Clutch	0.1733	0.1653	0.1248	0.2085	**0.6836**
2000 rpm	Normal	**0.7258**	0.0273	0.0991	0.1997	0.1155
	Pulley	0	**0.8760**	0	0.0766	0.1163
	Belt	0.1006	0.1474	**0.7555**	0.0380	0.2292
	Air	0.1983	0.1846	0	**0.7205**	0.0187
	Clutch	0.0975	0.1452	0.1899	0.0056	**0.7119**
2500 rpm	Normal	**0.7703**	0.0676	0.0836	0.1122	0.2659
	Pulley	0	**0.6470**	0.0640	0.2315	0
	Belt	0.0805	0.2228	**0.7233**	0.1323	0.2442
	Air	0	0.1207	0.0555	**0.7630**	0.0584
	Clutch	0.2621	0.0715	0.2556	0.0744	**0.7270**
3000 rpm	Normal	**0.7551**	0	0.0651	0	0.3291
	Pulley	0	**0.8143**	0.1052	0.1298	0.0825
	Belt	0	0.0972	**0.7559**	0.1223	0.3124
	Air	0	0.1642	0.1134	**0.8489**	0.2022
	Clutch	0.0341	0	0.2208	0.0749	**0.7573**
3500 rpm	Normal	**0.7441**	0	0.1331	0.2122	0.2880
	Pulley	0	**0.7746**	0.1247	0	0
	Belt	0.0824	0.0886	**0.8140**	0.0324	0.4255
	Air	0.1327	0	0.1542	**0.7590**	0.3111
	Clutch	0.0644	0	0.2380	0.2244	**0.8184**
Run-up	Normal	**0.7265**	0.0517	0.1525	0.2855	0.1209
	Pulley	0.0118	**0.4940**	0.2737	0.1444	0.1097
	Belt	0.1121	0.3728	**0.6823**	0.1996	0.1259
	Air	0.1577	0.2550	0.2338	**0.6522**	0.0454
	Clutch	0.1678	0.2025	0.1815	0.2047	**0.7268**

$$\text{error} = \sum_{i=1}^{l}\sum_{j=1}^{m}(d_{ij} - \hat{d}_{ij})^2, \quad (18)$$

where d_{ij} is the membership value of the ith calculation result that is inferred to the jth fault. $\hat{d}_{ij}$ is the true membership value of the ith practical data relative to the jth fault. The parameters l and m are the numbers of the fault condition and test data, respectively. Assuming every fault condition has three data to establish a knowledge base, the membership values of the true consequence form $\hat{d}_{ij}$ in this system are summarized in Table 3. The optimum n value is the minimum error in estimation of the knowledge base. Fig. 7(a) is the performance of membership function versus the parameter n with the triangular membership function under the idling engine operation condition. The definition of optimum inference error versus n value with the π membership function under the idling operation condition is shown as Fig. 7(b). In the figure, the optimum $n = 2$ is relative to Table 2. When $n = 2$ the results of fault conditions have a higher resolution with the π membership function at an idling engine operation schedule system.

5. Results and discussion

This section will describe the results of the proposed fault diagnosis system in a scooter platform under various operating conditions. A conventional adaptive order tracking fault diagnosis technique is carried out using visual inspection of the order amplitude figure under different fault conditions. Obviously, different faults in the mechanical system occur with different amplitudes in order figures. Unfortunately, the conventional inspection is not a precise approach for damage diagnosis. In the present study, the order amplitude figures of scooter acoustic emission are used for the data bank in the proposed fuzzy-logic inference for the intelligent fault diagnosis system. The order amplitude figures of scooter acoustic emission in the idling condition with various faults in the platform are shown as Fig. 8. Although by observing Fig. 8(a), we can infer normal conditions and pulley damage conditions using visual comparison, however, for other fault conditions such as belt damage, air leakage of intake and clutch damaged as shown in Fig. 8(b)–(d), there are too many order figures to infer the fault conditions using only visual comparison. Therefore, the fuzzy-logic inference is used to automatically increase the accuracy of the classification faults in the intelligent fault diagnosis system. The data bank also includes other amplitude figures of order tracking under various operating conditions shown in Figs. 9–13, which includes 2000 rpm, 2500 rpm, 3000 rpm, 3500 rpm and run-up engine operating conditions. Therefore, this research employs fuzzy-logic inference to establish data bank verification of the synthetic system under various operating conditions. The different data banks organize the inference rules and knowledge base of fuzzy logic inference respectively. Estimating the optimum inference error versus n value can increase the resolution of the diagnostic system. Under various operating conditions with two different membership functions, inference rules evaluate the optimum n values which are summarized in Table 5. According to the results of Table 4, the membership values are calculated with fuzzy logic inference accurately and conveniently.

Meanwhile, the triangular and π membership functions are compared in the fuzzy-logic inference under various engine operating conditions. The results of faults classification under various engine operating conditions using the triangular and π membership functions are summarized in Tables 5 and 6. The data showed that both the triangular and π membership functions are effective for fault classification in various fault conditions. In particular, the run-up operation schedule is emphasized in this research, the scooter engine can be operated by running up or casting down under practical condition. The run-up operation schedule has fine result by inferring the faults successfully.

The triangular membership function is applied when tolerance of fault is large and the π membership function is applied in certain condition. From Table 4, we can find the π membership function with the same various engine operations has smaller n values than the triangular membership function. This is because the features of adaptive order tracking have critical tolerance of faults in the same fault conditions. From Tables 5 and 6, the π membership function has higher membership values of accurate classification than the triangular membership function at each fault condition under the idling engine operation. In other operations, the π membership function also has high resolution. The π membership function is more capable of handling the qualities for this experimental work than the triangular membership function. But the results of the two membership functions provide evidence that fuzzy logic inference is a useful fault diagnosis system.

Table 6
Faults classification under various engine operation conditions with π membership function

Engine operation	Test faults	Membership value of faults				
		Normal	Pulley	Belt	Air	Clutch
Idle	Normal	**0.8098**	0.0116	0.1478	0.1391	0.2003
	Pulley	0.1437	**0.8202**	0.3903	0.2634	0.2757
	Belt	0.1846	0.1826	**0.8476**	0.0968	0.2021
	Air	0.2287	0.1185	0.1092	**0.9104**	0.2538
	Clutch	0.1379	0.0780	0.2120	0.1643	**0.7143**
2000 rpm	Normal	**0.8385**	0.1334	0.1617	0.3303	0.1933
	Pulley	0.0144	**0.9457**	0.0693	0.1061	0.1523
	Belt	0.1183	0.3264	**0.8637**	0.0897	0.3306
	Air	0.2941	0.3046	0.0992	**0.8417**	0.1157
	Clutch	0.1246	0.3066	0.3683	0.1004	**0.8129**
2500 rpm	Normal	**0.8726**	0.1440	0.1532	0.2633	0.3881
	Pulley	0.0065	**0.7755**	0.1146	0.3110	0.0321
	Belt	0.1143	0.3565	**0.8353**	0.2370	0.2992
	Air	0.0785	0.2326	0.1079	**0.8817**	0.1158
	Clutch	0.3635	0.1909	0.3511	0.1980	**0.8430**
3000 rpm	Normal	**0.7920**	0.0321	0.0997	0.0374	0.4237
	Pulley	0.0046	**0.8555**	0.1441	0.1634	0.1047
	Belt	0.0319	0.1551	**0.7932**	0.1680	0.3456
	Air	0.0175	0.2044	0.1544	**0.8962**	0.2562
	Clutch	0.0762	0.0407	0.2520	0.1149	**0.8030**
3500 rpm	Normal	**0.7912**	0.0591	0.1843	0.2560	0.3564
	Pulley	0.0019	**0.8208**	0.1609	0.0086	0.0330
	Belt	0.1065	0.1653	**0.8705**	0.0828	0.4825
	Air	0.2133	0.0646	0.2111	**0.8044**	0.3707
	Clutch	0.1153	0.0762	0.3251	0.2481	**0.8724**
Run-up	Normal	**0.7671**	0.1395	0.2233	0.2603	0.1850
	Pulley	0.0550	**0.5206**	0.2954	0.1866	0.2206
	Belt	0.1757	0.4317	**0.7016**	0.2116	0.2671
	Air	0.1740	0.2849	0.3192	**0.7006**	0.1295
	Clutch	0.2276	0.3414	0.2555	0.2922	**0.7214**

6. Conclusions

In the present study, a prototype of an expert system for fault diagnosis in scooters platform using fuzzy-logic interference with adaptive order tracking technique is developed. The adaptive order tracking based on Kalman filter extracts the order features of the scooter test platform. They then are used for creating the data bank in the proposed intelligent fault diagnosis system. Fuzzy logic inference is used for fault classification in the proposed system. The experimental results indicated that the proposed system is effective for increasing the accuracy of fault diagnosis under various operation conditions.

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