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A novel identification method of Volterra series in rotor-bearing system for fault diagnosis

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ABSTRACT

Volterra series is widely employed in the fault diagnosis of rotor-bearing system to prevent dangerous accidents and improve economic efficiency. The identification of the Volterra series involves the infinite-solution problems which is caused by the periodic characteristic of the excitation signal of rotor-bearing system. But this problem has not been considered in the current identification methods of the Volterra series. In this paper, a key kernels-PSO (KK-PSO) method is proposed for Volterra series identification. Instead of identifying the Volterra series directly, the key kernels of Volterra are found out to simply the Volterra model firstly. Then, the Volterra series with the simplest formation is identified by the PSO method. Next, simulation verification is utilized to verify the feasibility and effectiveness of the KK-PSO method by comparison to the least square (LS) method and traditional PSO method. Finally, experimental tests have been done to get the Volterra series of a rotor-bearing test rig in different states, and a fault diagnosis system is built with a neural network to classify different fault conditions by the kernels of the Volterra series. The analysis results indicate that the KK-PSO method performs good capability on the identification of Volterra series of rotor-bearing system, and the proposed method can further improve the accuracy of fault diagnosis.

1. Introduction

Fault diagnosis of rotor-bearing system is essential to prevent dangerous accidents and improve economic efficiency. As a hot research topic, it has been studied by many academics, and most of the methods can be separated into two major categories: signal processing method and modeling method [1]. As the modeling method has favorable performance in considering the parameters characteristic of different rotor-bearing system, it has gained attractive and wide attention.

The critical problem of modeling method is the determination of the mathematical structure of a physical system from input–output measurement [2]. As a mature theory, linear ARMA model has been employed for fault diagnosis in rotor-bearing system [3–5]. But the ARMA model doesn't have a good performance in the description of the dynamic behavior of the rotor-bearing system, because there are many nonlinear factors which may cause nonlinear vibration, such as the stiffness and damping.

With the development of the nonlinear theory, Volterra series has been widely applied in the modeling and faults diagnosis of nonlinear system. The multidimensional Fourier transformation of the Volterra kernels which is defined as the

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generalized frequency response function (GFRF) has been widely employed in the analysis of nonlinear system [6,7]. The GFRF can describe the nonlinear response effectively in the frequency domain. But the high-dimensional GFRF has less performance in the way of intuitive, and GFRF always encounter the problem of disaster of dimensionality. Nonlinear Output Frequency Response (NOFRFs) as a transformation of GFRF has gained attractiveness of many researchers [8–11]. The NOFRFs provide a simple description of the frequency domain behaviors of nonlinear system, and it has a very good performance in fault diagnosis. But this method needs multi sinusoidal excitation in the same frequency and different amplitude. The excitation limitation makes troublesome in operation and online fault diagnosis. The time-domain Volterra series has intuitive in its structure, and it is useful for online fault diagnosis. The time-domain Volterra series will also encounter the problem of disaster of dimensionality. So, there is an urgent demand for effective identification methods.

Many identification methods have been proposed for the Volterra series of rotor-bearing system [1,12–19]. A blind quadratic modeling method based on HOS was proposed to detect the mechanical fault [5]. A LMS variant method was used to estimate second-order Volterra system parameters from noisy measurements [12]. These classical identification methods transform the input-output signal into the matrix form, and the Volterra's kernels is identified with the least squares method. But the input signal of rotor-bearing system is a periodic signal. The undetermined characteristic leads to the traditional identification method inefficiency. Some intelligent identification methods have also been employed. Genetic algorithm (GA) was used to identify the Volterra kernels for fault diagnosis [1]. Yang et al. used particle swarm optimization (PSO) to identify the Volterra series [13]. Although these intelligent methods approach the model well, the result of identification is not unique. So there is an urgent need to develop a new identification method that considers the periodic input signal for the Volterra series of rotor-bearing system.

In this paper, a key kernels-PSO (KK-PSO) method is proposed to identify the Volterra series of rotor-bearing system. Instead of identifying the Volterra series with intelligent methods directly, the influence of each kernel of the Volterra series is calculated firstly. Then, the key kernels are found to simplify the Volterra series. Next, the Volterra series is identified by the PSO method. The new method is compared with orthogonal least squares method and traditional PSO method through simulation verification. The results show that the KK-PSO is accurate and reliable. Finally, the proposed method is applied to identify the Volterra series of a rotor-bearing test rig. And fault classification is further done on the test rig with a neural network.

The rest of this paper is organized as follows: A brief introduction of the problem in identification of the Volterra series is described in Section 2. In Section 3, the KK-PSO method for identification of the Volterra series is presented and fault diagnosis method by kernels classification with neural network is also introduced. Simulation verification and experimental tests on rotor test rig are present in Section 4. Finally, conclusions from this research as well as the advantages and limitations of the proposed method are discussed in Section 5.

2. Statement of problems

In real world, many engineering problems represent nonlinear behavior. Most nonlinear models in engineering and science can be described by a second order Volterra series [5].A single input signal output (SISO) Volterra series is considered as follows:

$$\mathbf{y}(n) = \sum_{l_0=0}^{M-1} \mathbf{h}_1(l_0)\mathbf{u}(n-l_0) + \sum_{l_1=0}^{M-1}\sum_{l_2=0}^{M-1} \mathbf{h}_2(l_1,l_2)\mathbf{u}(n-l_1)\mathbf{u}(n-l_2) \tag{1}$$

where $\mathbf{u}$ is the input signal, $\mathbf{y}$ is the output signal, M represents the memory length, $\mathbf{h}$ denotes the kernels of the system.

In order to express Eq. (1) in concise modality, the kernels $\mathbf{h}$ and input $\mathbf{u}$ are expanded into $\mathbf{H}$ and $\mathbf{U}(n)$, and $\mathbf{H}$, $\mathbf{U}(n)$ can be defined as:

$$\begin{aligned}\mathbf{H} = \big[&\mathbf{h}_1(0), \mathbf{h}_1(1), \ldots, \mathbf{h}_1(M-1), \ \vdots\ \mathbf{h}_2(0,0), \mathbf{h}_2(0,1), \ldots, \mathbf{h}_2(0,M-1),\\ &\mathbf{h}_2(1,1), \ldots, \mathbf{h}_2(M-1,M-1)\big]^T\end{aligned} \tag{2}$$

$$\begin{aligned}\mathbf{U}(n) = \Big[&\mathbf{u}(n), \mathbf{u}(n-1), \ldots, \mathbf{u}(n-(M-1)), \ \vdots\ \mathbf{u}(n)^2, \mathbf{u}(n)\mathbf{u}(n-1), \ldots,\\ &\mathbf{u}(n)\mathbf{u}(n-(M-1)), \mathbf{u}(n-1)^2, \ldots, \mathbf{u}(n-(M-1))^2\Big]\end{aligned} \tag{3}$$

$\mathbf{H}$, $\mathbf{U}(n)$, can be separated into two parts: The first order part and second order part. The dimension of $\mathbf{H}$ and $\mathbf{U}(n)$ is $(M^2/2+3M/2)\times 1$. Then, Eq. (1) can be described as the following matrix form:

$$\mathbf{y} = \mathbf{U} \times \mathbf{H} \tag{4}$$

Obviously, after expanding the input matrix and kernels matrix, the Volterra series can be considered as a linear model.

Many algorithms have been employed for identification of the Volterra series for example, ordinary least square (OLS), least mean square (LMS), recursive least square (RLS), as well as some evolution algorithms such as genetic algorithms (GAs), ant colony algorithm (AC), differential evolution (DE), and particle swarm optimization (PSO), etc. Most of these algorithms consider $\mathbf{u}$ as a Random process or Gaussian Random process, but the input signal $\mathbf{u}$ in rotor-bearing system is a periodic signal. Then the input matrix $\mathbf{U}$ is a singular matrix, which leads to the identification of the Volterra model impossible or can't get the best Volterra model. This defect limits the development of fault diagnosis in rotor-bearing system.

3. System identification and fault diagnosis by KK-PSO method with neural network

3.1. Identification of Volterra series with KK-PSO method

As the statement of problems above, a new KK-PSO method is proposed to overcome the limitations. The purpose of the new method is to find the kernels which are the key elements of the models. Then the model is simplified. The steps of this method are as follows:

Step 1 According to Eq. (4), the Volterra series can be treated as a linear model. How much the each column of $\mathbf{U}(n)$ influence on $\mathbf{y}(n)$ is quantitative calculated, i.e., the relevance between each column of $\mathbf{U}(n)$ and output $\mathbf{y}(n)$ is calculated. Here, the MSE (mean square error) is used to evaluate the influence.
$\mathbf{U}_i$ is described as a matrix which $\mathbf{U}(n)$ retain the ith column and the other elements is set as zero:

$$\mathbf{y} = \mathbf{U}_i \times \mathbf{H}, \quad i = 1, 2, 3 \ldots \left(M^2/2 + 3M/2\right) \tag{5}$$

The PSO algorithm is employed to find the best $\mathbf{H}^*$ according to Eq. (5). Then, the MSE of each column is calculated as Eq. (6).

$$MSE = \frac{(\mathbf{U}_i\mathbf{H}^*)^T \times (\mathbf{U}_i\mathbf{H}^*)}{n} \tag{6}$$

Step 2 Columns which have smaller MSE make a major influence on the output. For each order of columns, the MSE is ranked from smallest to largest. The initialization matrix $\mathbf{V}$ which is separate into the first order part and second order part is set as:

$$\mathbf{V} = [0 : 0]$$

The process to confirm the key kernels is shown in Fig. 1, where σ is the permissible error for modeling the Volterra series.
Then the matrix $\mathbf{V}$ has been confirmed with the least input matrix to model the Volterra series, and $\mathbf{H}'$ which the matrix

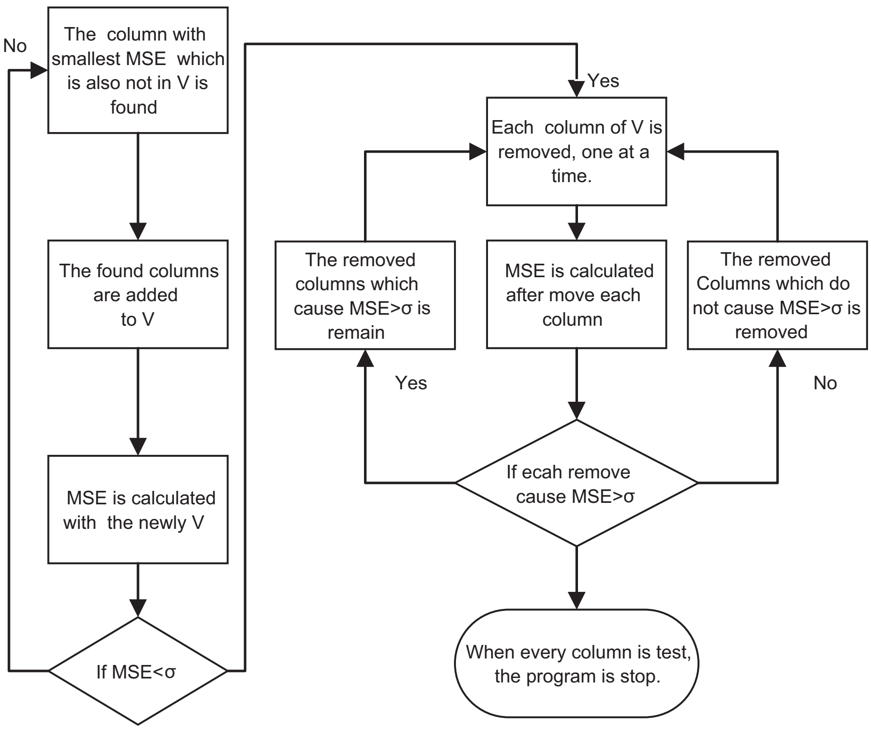

Fig. 1. Process of identification the key kernels.

V is correspondent to, would be the key kernels. Thus the Volterra series can be expressed in the simplest or unique formation as follows:

$$\mathbf{y} = \mathbf{V} \times \mathbf{H}'$$

Step 3 After the simplification of the Volterra series, the PSO algorithm is used to identify the key kernels directly. Obviously, the simplest or unique Volterra series can be identified by the KK-PSO method.

3.2. Fault diagnosis by kernels classification with neural network

Many researches indicate that the linear and nonlinear behavior of the system will change obviously when faults happen in rotor-bearing system. And the time domain kernels of the Volterra series will reflect this change in its position and amplitude. So, the kernels can be used as feature for fault diagnosis.

Neural network can simulate the neural network behavior characteristics of animal, with functions of striking self-learning, thinking, reasoning, judging, and memorizing. The network depends on the complexity of the system. By adjusting the internal connection relationship of a large number of nodes, it can perfectly process the relationship between the input and output. As an effective classification method, neural network is widely used in feature identification, image recognition, etc.

In this paper, the neural network is proposed and employed to the fault classification in rotor-bearing system. As represented in Fig. 2, the kernels matrix is set as an input terminal of the neural network. P represents the number of neurons in the hidden layer. N represents the number of output neurons, corresponding to N states.

4. Simulation verification and experimental tests

In this section, a simulation is firstly performed to test the efficiency of the KK-PSO method, meanwhile comparing it with the least squares methods and the traditional PSO identification method. Then, model identification and kernels classification are performed for fault diagnosis on a rotor-bearing test rig.

4.1. Simulation verification

In order to demonstrate the effectiveness of the identification methods under a periodic input signal. A second order Volterra series is considered for simulation verification. The Volterra series and input signal $u(n)$ is expressed as follows:

$$\begin{aligned} y(n) &= 0.6u(n) + 1.2u^2(n-1) + 0.8u(n-1)u(n-2) \quad n = 1, 2, \ldots \\ u(n) &= 5\ \sin(0.05\pi \times n) \end{aligned} \tag{7}$$

1024 groups of input–output data are produced according to Eq. (7). The identifying sample is organized by the data numbered 201 to 400. The testing sample is organized by the data numbered 501 to 700.

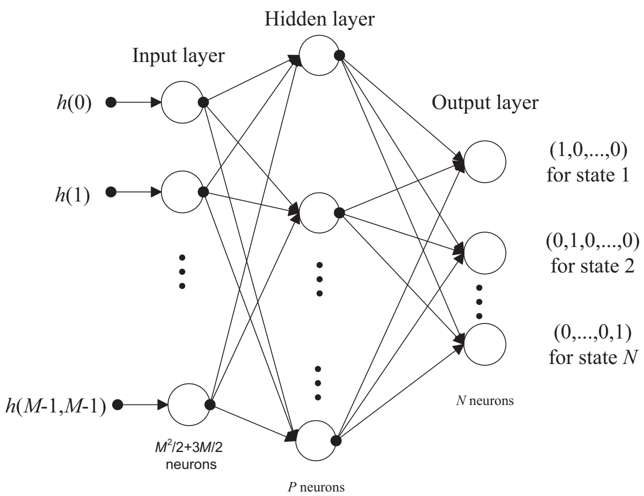

Fig. 2. Fault classification by kernels with neural network.

As a classical identification method, least square method is used to approach the Volterra series first. The first order memory and second order memory length is set as 5. The kernels matrix $\mathbf{H}$ is built base on Eq. (2). The input matrix $\mathbf{U}(n)$ and output matrix $\mathbf{y}(n)$ is also built with the input-output data base on Eq. (1) and Eq. (3). Then, the kernels matrix $\mathbf{H}$ can be solved based on Eq. (4). According to the ordinary least square method, the kernels can be identified by the following equation, as:

$$\mathbf{H} = (\mathbf{U}^T\mathbf{U})^{-1} \times \mathbf{U}^T \times \mathbf{y} \tag{8}$$

Because the input signal is a sinusoidal signal, the column-dependence of the input matrix $\mathbf{U}(n)$ lead to Eq. (4) underdetermined. Therefore, there are infinite solutions, and Eq. (8) can't be solved with the ordinary least square method directly. So, the orthogonal least square method is employed to overcome this problem. The left division method which is belong to orthogonal least square method is utilized to get the least-squares solution of the underdetermined system, as follow:

$$\mathbf{H} = \frac{\mathbf{U}}{\mathbf{y}} \tag{9}$$

The identification result by Eq. (9) is shown as:

$$\begin{aligned} y(n) = {} & 1.1413u(n-2) - 0.6u(n-4) + 0.7717u^2(n) + 0.3922u(n)u(n-4) \\ & + 0.9732u(n-2)u(n-2) - 0.072u(n-4)u(n-4) \end{aligned}$$

In addition, the minimal norm least squares which is belong to orthogonal least square method solution is also presented, as Eq. (10):

$$\mathbf{H} = \mathbf{U}^+ \times \mathbf{y} \tag{10}$$

where $\mathbf{U}^+$ is the Moore–Penrose inverse of matrix $\mathbf{U}(n)$. The minimal norm least squares solution is as follow:

$$\begin{aligned} y(n) = {} & 0.3528u(n) + 0.2393u(n-1) + 0.1199u(n-2) - 0.0025u(n-3) - 0.1248u(n-4) \\ & + 0.3461u^2(n) + 0.2923u(n)u(n-1) + 0.2312u(n)u(n-2) + 0.1644u(n)u(n-3) \\ & + 0.0936u(n)u(n-4) + 0.2434u(n-1)u(n-1) + 0.1886u(n-1)u(n-2) \\ & + 0.1291u(n-1)u(n-3) + 0.0664u(n-1)u(n-4) + 0.1413u(n-2)u(n-2) \\ & + 0.0905u(n-2)u(n-3) + 0.0376u(n-2)u(n-4) + 0.0498u(n-3)u(n-3) \\ & + 0.0078u(n-3)u(n-4) - 0.0222u(n-4)u(n-4) \end{aligned}$$

Fig. 3 presents the test output comparison of the identification model and the original model. The results show that the outputs of the both identification model are very close to the original model. But the structures of both identification model are very different to the original model which makes difficult for the following fault diagnosis. So, the orthogonal least

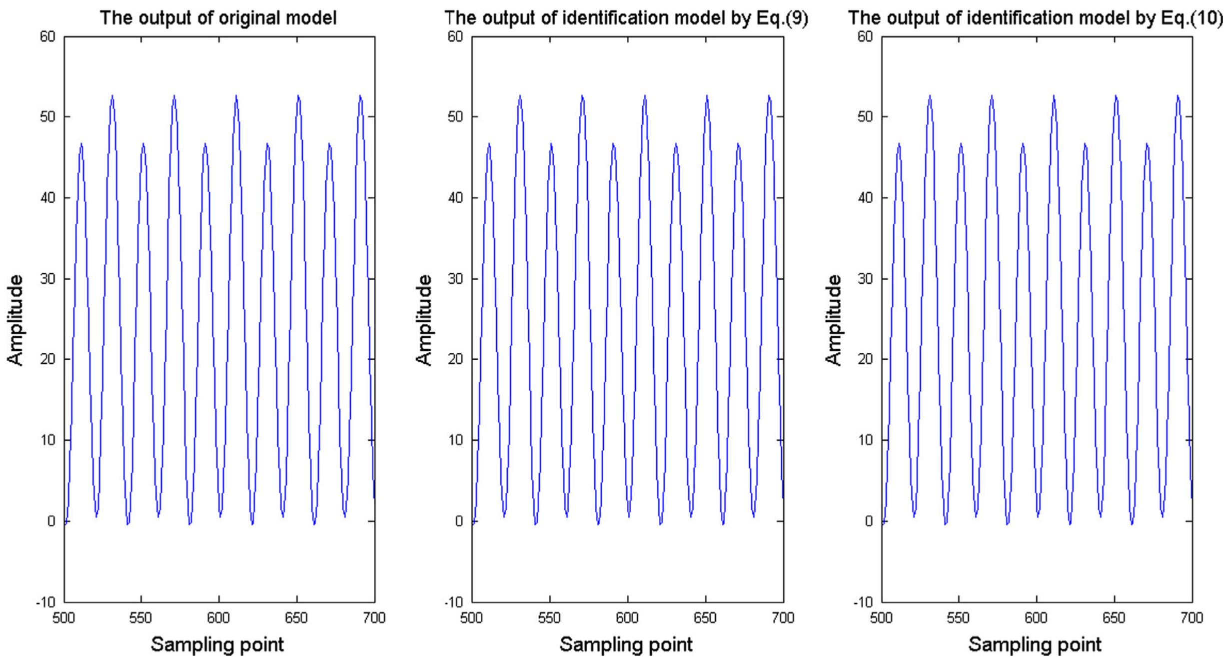

Fig. 3. Test output comparison of the original model and the identification model with least squares.

Table 1
Parameters of system identification.

Parameters of volterra series		**Parameters of PSO**				
Max time lag	Size of **H**	Pop size	Inertia weight w	Two acceleration coefficients		Computation max error σ
5	20	300	0.7 to 0.2	1.49	1.49	0.05

Table 2
The identification results with PSO method in 3 times.

	$h(0)$	$h(1)$	$h(2)$	$h(3)$	$h(4)$	$h(0,0)$	$h(0,1)$	$h(0,2)$	$h(0,3)$	$h(0,4)$
Model 1	−0.023	1.318	−1.332	1.169	−0.560	−0.220	1.522	1.847	0.589	−1.025
Model 2	1.951	−1.942	−0.632	1.922	−0.658	0.904	0.168	−1.221	0.015	0.731
Model 3	0.275	−0.443	0.359	1.782	−1.438	0.409	−1.104	1.367	0.838	0.179
$h(1,1)$	$h(1,2)$	$h(1,3)$	$h(1,4)$	$h(2,2)$	$h(2,3)$	$h(2,4)$	$h(3,3)$	$h(3,4)$	$h(4,4)$	**MSE**
−0.880	−1.450	0.851	1.898	0.239	−1.662	−0.665	0.792	0.198	0.113	0.0016
0.923	−0.635	0.982	0.984	1.724	−1.544	−0.365	−1.704	0.523	0.706	0.007
1.114	−0.452	−1.281	1.002	1.089	−0.336	−1.308	0.847	−1.906	1.658	0.0045

Table 3(a)
The MSE of each column.

column	1	2	3	4	5	6	7	8	9	
The kernels correspond	$h(0)$	$h(1)$	$h(2)$	$h(3)$	$h(4)$	$h(0,0)$	$h(0,1)$	$h(0,2)$	$h(0,3)$	
MSE*200	185902	185924	185988	186088	186213	9511	3904	1250	2042	
10	11	12	13	14	15	16	17	18	19	20
$h(0,4)$	$h(1,1)$	$h(1,2)$	$h(1,3)$	$h(1,4)$	$h(2,2)$	$h(2,3)$	$h(2,4)$	$h(3,3)$	$h(3,4)$	$h(4,4)$
7218	1144	1459	5004	12262	4779	11054	20422	19718	30858	43175

Table 3(b)
The process of KK-PSO method.

Process	**Matrix V**	**Kernels**	**MSE**
Initialization **V**	$\mathbf{V}=[0:\ 0]$	$\mathbf{H}=[0:\ 0]$	934
Columns are added to **V**	$\mathbf{V}=[1:\ 11]$	$\mathbf{H}=[0.6:\ 1.99]$	1.22
	$\mathbf{V}=[1,2:\ 11,8]$	$\mathbf{H}=[0.577,\ 0.024:\ 1.1,0.914]$	1.32
	$\mathbf{V}=[1,2,3:\ 11,8,12]$	$\mathbf{H}=[0.395,0.37,-0.17:\ 0.814,0.322,0.874]$	0.024
Columns are removed from **V**	$\mathbf{V}=[1,2:\ 11,8,12]$	$\mathbf{H}=[0.626,\ -0.026:\ 0.991,0.201,0.813]$	0.0056
	$\mathbf{V}=[1:\ 11,8,12]$	$\mathbf{H}=[0.601:\ 1.68,\ -0.425,0.734]$	0.031
	$\mathbf{V}=[1:\ 11,12]$	$\mathbf{H}=[0.599:\ 1.21,0.789]$	2.5×10^{-4}

square method is useful to approach the output of the original model, but it is not appropriate to identify the structure of the original model.

In order to overcome the above problem, PSO method and KK-PSO method are utilized in the identification of Eq. (7). The PSO method is to find the optimizing kernels matrix directly with the input–output data. The KK-PSO method was introduced before.

Some parameters need to be set before the identification process, such as the max time-lag of the Volterra series and PSO parameters. These parameters directly affect the calculation time and accuracy of modeling. First, large memory size can describe the Volterra series more approachable, but it leads difficulty in calculation, and the large size of kernels makes the fault diagnosis complexity. Second, parameters of the PSO algorithm will affect the optimized speed and accuracy. Shi and Eberhart [20] have analyzed the effect of the inertia weight through empirical experiments, and found that a larger inertia weight can bring a better global convergent ability while a smaller inertia weight can manipulate a better local search. Large pop size can bring a better optimization result but also take more time for computation [21]. By comprehensive consideration, the parameters are set as presented in Table 1.

First, the traditional PSO method is used to identify the Volterra series in three times, and three different models (Model 1, Model 2, and Model 3) are get as showed in Table 2.

Second, the KK-PSO method is employed to identify the Volterra series. The MSE of each column is calculated as the process in Section 3.1. The results are showed in Table 3(a). Then the KK-PSO method is employed to identify the system. The calculation process is shown in Table 3(b).

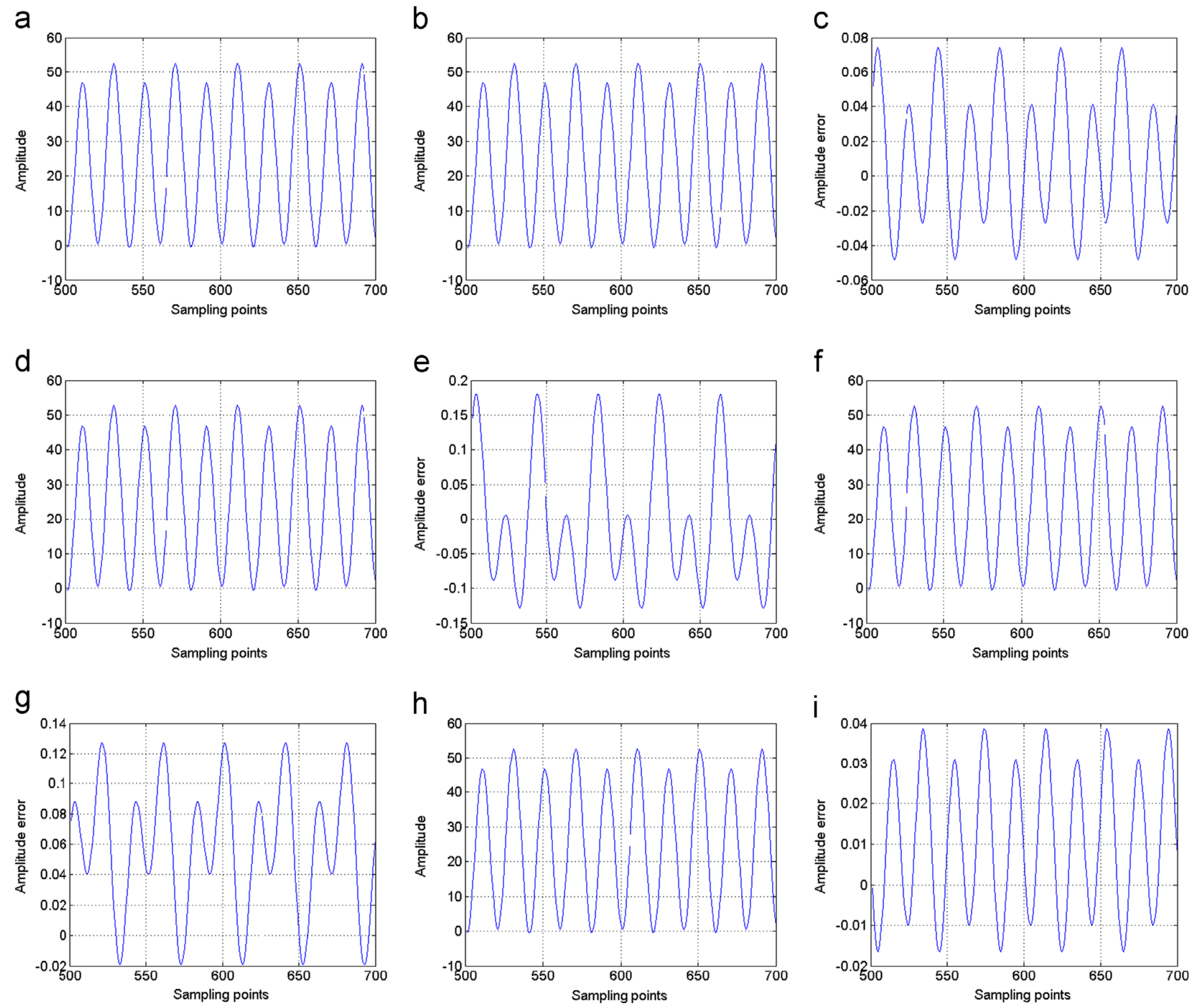

Fig. 4. Results of simulation. (a) Actual output of testing model, (b) and (c) output and residual error by Model 1, (d) and (e) output and residual error by Model 2, (f) and (g) output and residual error by Model 3, (h) and (i) output and residual error by Model 4.

In Table 3(b), the matrix **V** is separated into two parts (the first order and second order), and the numbers in **V** represent the *i*th column, **H** is the kernels which the matrix **V** is corresponding to.

So, the identification model (Model 4) of KK-PSO method can be described as:

$$y(n) = 0.599u(n) + 1.21u^2(n-1) + 0.789u(n-1)u(n-2)$$

Fig. 4(a) represents the actual output of the test model, Fig. 4(b), (d), (f) are the output of the three models which are identified by PSO method, and Fig. 4(c), (e), (g) are the residual errors of the three models. Fig. 4(h) shows the output of Model 4, Fig. 4(i) is the residual error of Model 4. It can be seen that even though the outputs of all the four models are very approachable to the actual output and have small residual errors, there are some defects in PSO method comparing to KK-PSO method.

(1) As showed in Fig. 5, the kernels of the three models which are identified by PSO have significant differences, although they describe the same system. The KK-PSO method can identify the unique model. And the model is approachable to Eq. (7) very well, not only in kernels' position but also in kernels' amplitude.
(2) The PSO method gets the Volterra series with a large amount of kernels comparing with KK-PSO method. Then, the kernels classification method cannot be employed for fault diagnosis directly. And other processes are required before fault diagnosis, such as generalized frequency response function (GFRF).

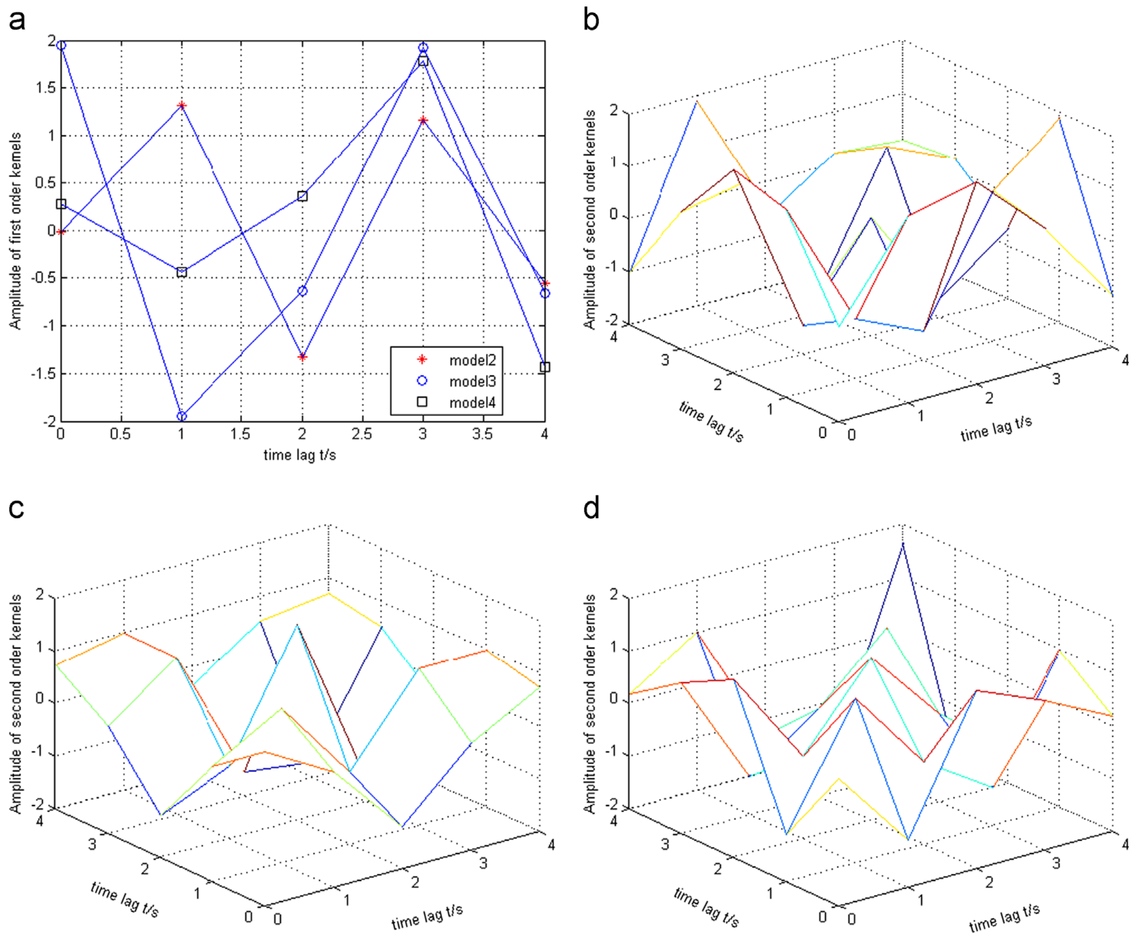

Fig. 5. Kernels of models which identified by PSO method, (a) the first order kernels of three models, (b) the second order kernels of Model 1, (c) the second order kernels of Model 2, (d) the second order kernels of Model 3.

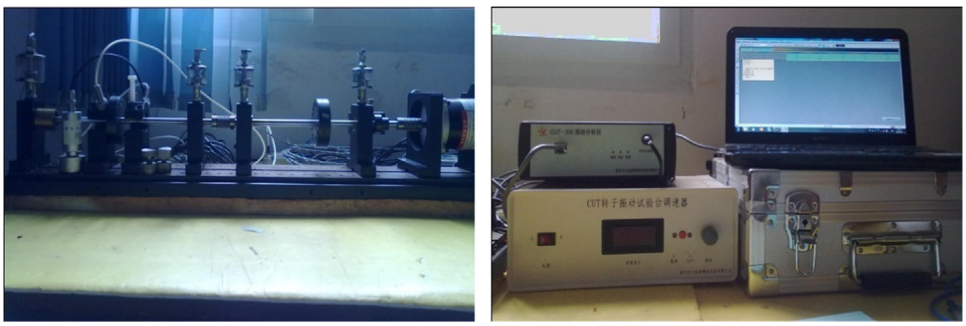

Fig. 6. Rotor test rig and signal collection device.

All these defects limit the development of system identification and fault diagnosis in rotor-bearing system.

The simulation results indicate that all of the identification models by orthogonal least square method, PSO method and KK-PSO method can approach the output of the original model very well. But the KK-PSO method is more appropriate to identify the structure of the original model than orthogonal least square method and PSO method. And the simulation verification further indicates the KK-SPO method has a strong capability on identification of the Volterra series under a periodic input signal.

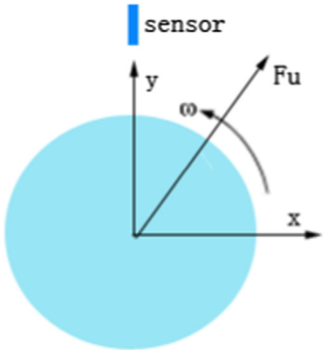

Fig. 7. The unbalance force on rotor.

4.2. Experimental tests

An experimental test has done on the rotor-bearing test rig (as showed in Fig. 6) to analyze the influence of Volterra kernels under different states, and fault diagnosis has been made forward.

The vibration of the test rig is excited by the excitation force as showed in Fig. 7. In this test rig, the mainly excitation force is caused by the unbalance mass. Then, the excitation force can be described as:

$$\mathbf{F}_u = M_e \omega^2 r \tag{11}$$

where M_e is unbalance mass, ω is the rotating speed, r is the eccentric radius.

In order to get the excitation force on the sensor direction, the excitation force is decomposed into x and y direction as showed in Fig. 7, expressed as:

$$\begin{cases} \mathbf{F}_{ux} = M_e \omega^2 r \ \sin(2\pi\omega t + \varphi) \\ \mathbf{F}_{uy} = M_e \omega^2 r \ \cos(2\pi\omega t + \varphi) \end{cases} \tag{12}$$

where φ is the initial phase. And the force on y direction is the excitation force which influences the vibration of the y axis. Therefore, the input excitation force is $\mathbf{F}_{uy}$, and the output is the vibration data which are collected by the sensor.

In this experimental test, three different states have been made on the test rig, including two different out-of-balance states and rotor-to-stator rub state. First, the test rig is operated at the original state (under the initial unbalance mass). The initial unbalance mass is 1 g. Second, screws are added on the disk to change the unbalance mass, and get another unbalance state. The unbalance mass is 3 g. Finally, the screws are removed and a stick is used to rub the rotating rotor as rotor-to-stator rub state, the excitation force is the initial unbalance mass. The running speed is 3000 rpm/min. The sampling frequency is 128 points per round, and 4 rounds of data are used as a group. For each state, 10 groups of data are collected. The input and output signal for each state is shown in Fig. 8.

Models of each state are identified by using the KK-PSO method. And the parameters of the method are set, as shown in Table 4:

In order to build a fault diagnosis system based on neural network, 7 groups of kernels of models in each state are used to train the neural network. Then 3 groups of kernels of models in each state are used to test the efficiency of the diagnosis method. The results are shown in Table 5:

The results indicate that the neural network can classify different states effectively, and verify the accurate and reliable of KK-PSO method forward.

5. Conclusion

In this paper, a KK-PSO method is proposed for the identification of the Volterra series of rotor-bearing system. The analysis results indicate that the irritating infinite-solution problems in the traditional identification methods can be resolved effectively by the KK-PSO method.

The proposed method consists of a two-step procedure: In the first step, the influence of each kernel of the Volterra series is quantitative calculated. And the key kernels are found to simplify the Volterra series. In the second step, the Volterra series is identified by the PSO method directly. The simulation verification showed that the proposed method has a strong effect on identification of the Volterra series by comparison to the LS method and normal PSO method. Moreover, the KK-PSO method is applied to get the Volterra series of a rotor-bearing test rig in different states, and a fault diagnosis system is built with a neural network to classify different fault by the kernels of the Volterra series. The results indicate that the proposed method has a good performance in the fault diagnosis of rotor-bearing system.

Future research is to improve the computational efficiency and apply this method to practical engineering diagnostic cases.

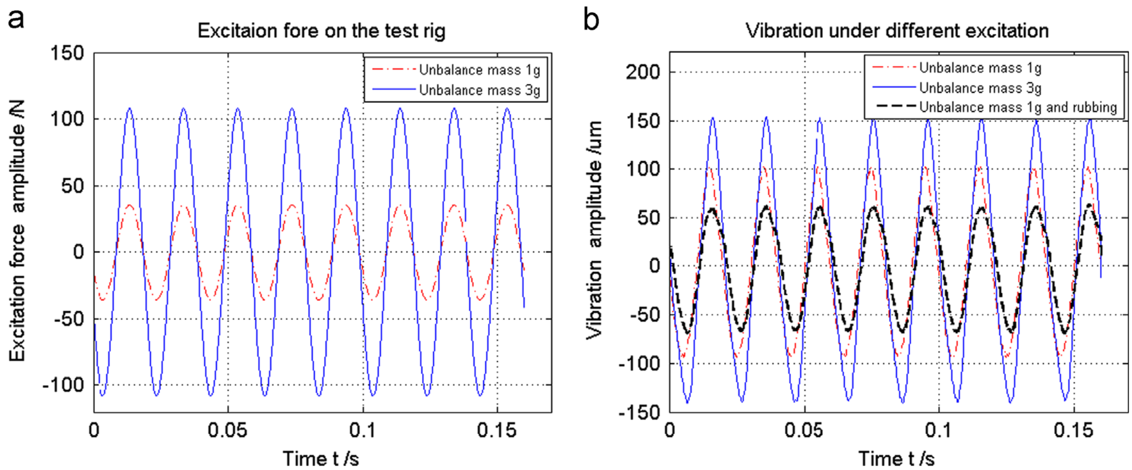

Fig. 8. Input excitation fore and output vibration of rotor-bearing system in different states: (a) input excitation fore (b) output vibration.

Table 4
Parameters of volterra series and identify method.

Parameters of volterra series		**Parameters of PSO**				**Parameters of neural network**		
Max Time lag	Size of **H**	Pop size	Inertia weight *w*	Two acceleration coefficients		Input layer	Hidden layer	Output layer
10	65	300	0.7 to 0.2	1.49	1.49	65	15	3

Table 5
Results of fault diagnosis by neural network.

States	**Test sample**	**Result of neural network**
Out-of-balance (1g)	1	[0.918; 0.017; 0.031]
	2	[0.937; 0.128; 0.005]
	3	[0.922; 0.045; 0.023]
Out-of-balance (3g)	1	[0.066; 0.970; 0.036]
	2	[0.082; 0.985; 0.031]
	3	[0.013; 0.983; 0.055]
Rotor-to-stator	1	[0.085; 0.212; 0.942]
	2	[0.127; 0.096; 0.931]
	3	[0.034; 0.188; 0.886]

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References

[1] H. Tang, Y.H. Liao, J.Y. Cao, H. Xie, Fault diagnosis approach based on Volterra models, Mech. Syst. Signal Pr 24 (4) (2010) 1099–1113.
[2] Bachschmid N., Pennacchi P., Model-based malfunction identification from bearing measurements, in: Imeche Conference Transactionn. 6 (2000) 571-580.
[3] Hong Thom Pham, Bo-Suk Yang, Estimation and forecasting of machine health condition using ARMA/GARCH model, Mech. Syst. Signal Pr. 24 (2) (2010) 546–558.
[4] Tommy WS Chow, Hong-Zhou Tan, Semiblind identification of nonminimum-phase ARMA models via order recursion with higher order cumulants, IEEE Trans. Ind. Electron 45 (4) (1998) 663–671.
[5] Tommy WS Chow, Hong-Zhou Tan, HOS-based nonparametric and parametric methodologies for machine fault detection, IEEE Trans. Ind. Electron. 47 (5) (2000) 1051–1059.
[6] S.A. Billings, J.C. Peyton Jones, Mapping non-linear integro-differential equations into the frequency domain, Int. J. Control 52 (4) (1990) 863–879.

[7] O.M. Boaghe, S.A. Billings, L.M. Li, P.J. Fleming, J. Liu, Time and frequency domain identification and analysis of a gas turbine engine, Control Eng. Pract. 10 (12) (2002) 1347–1356.
[8] Z.Q. Lang*, S.A. Billings, Energy transfer properties of non-linear systems in the frequency domain, Int. J. Control 78 (5) (2005) 345–362.
[9] Z.K. Peng, Z.Q. Lang, S.A. Billings, Crack detection using nonlinear output frequency response functions, J. Sound Vib. 301 (3) (2007) 777–788.
[10] J. Cao, L. Chen, J. Zhang, W. Cao, Fault diagnosis of complex system based on nonlinear frequency spectrum fusion, Measurement 46 (1) (2013) 125–131.
[11] Z.K. Peng, Z.Q. Lang, Detecting the position of non-linear component in periodic structures from the system responses to dual sinusoidal excitations, Int. J. Nonlin. Mech. 42 (9) (2007) 1074–1083.
[12] Z. Sigrist, E. Grivel, B. Alcoverro, Estimating second-order Volterra system parameters from noisy measurements based on an LMS variant or an errors-in-variables method, Signal Process 92 (4) (2012) 1010–1020.
[13] Yi-Sung Yang, Wei-Der Chang, Teh-Lu Liao, Volterra system-based neural network modeling by particle swarm optimization approach, Neurocomputing 82 (2012) 179–185.
[14] Animesh Chatterjee, Nalinaksh S Vyas, Non-linear parameter estimation with Volterra series using the method of recursive iteration through harmonic probing, J. Sound Vib. 268 (4) (2003) 657–678.
[15] Animesh Chatterjee, Nalinaksh S Vyas, Convergence analysis of Volterra series response of nonlinear systems subjected to harmonic excitation, J. Sound Vib. 236 (2) (2000) 339–358.
[16] A.A. Khan, N.S. Vyas, Application of Volterra and Wiener theories for nonlinear parameter estimation in a rotor-bearing system, Nonlin. Dyn. 24 (3) (2001) 285–304.
[17] Stephen Boyd, Y.S. Tang, L.O. Chua, Measuring Volterra kernels, circuits and systems, IEEE Trans. Circuits 30 (8) (1983) 571–577.
[18] V. John Mathews, Orthogonalization of correlated Gaussian signals for Volterra system identification, Signal Process 2 (10) (1995) 188–190.
[19] Ceri Evans, et al., Periodic signals for measuring nonlinear Volterra kernels, IEEE Trans. Instrum. Meas. 45 (2) (1996) 362–371.
[20] Shi, Yuhui, Russell C. Eberhart, Empirical study of particle swarm optimization, in: Proceedings of the 1999 Congress on Evolutionary Computation. 3 (1999) 1945-1950.
[21] Kennedy, James, Particle Swarm Optimization, Encyclopedia of Machine Learning. (2010) 760-766.