Sensors & Transducers, Vol. 179, Issue 9, September 2014, pp. 72-78

Sensors & Transducers

Performance Degradation Assessment Method for Cracked Rotor Based on Multi-observation Hidden Markov Model

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Received: 21 June 2014 /Accepted: 29 August 2014 /Published: 30 September 2014

Abstract: Reliability of rotating machinery has a significant relation with personal safety and economic efficiency. With the development of science and technology, the improvement of performance degradation of machinery becomes increasingly higher. Research of traditional reliability theory depends on failure data. Some lifetime data result in little or even no failure. For mechanical equipment, degradation data may contain useful information about machinery reliability. Service condition of rotating machinery suffers from a long period of deterioration time until functional failure occurs. However, normal or failure status of rotating machinery is simply defined by traditional fault diagnosis methods. A machinery performance degradation assessment method for the cracked rotor based on multi-observation Hidden Markov Model is proposed for rotating machinery in run-up and shutdown processes. The proposed method can reflect the change of the performance of rotating machinery effectively. Finally, dynamics simulation data of the cracked rotor with gradually decreasing stiffness is used to validate the feasibility of the proposed method. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Performance degradation assessment, Rotor, Rotating machinery, Dynamic model, Multi-observation hidden Markov model.

1. Introduction

During operation, rotating machinery often undergoes a series of degradation conditions. When the degradation value reaches a certain threshold, faults or failures may occur. In recent decades, accidents concerning rotating machinery are frequently reported, of which a number of catastrophic accidents are caused by cracked rotors. Thus, the usage of modern vibration testing and analysis techniques of online monitoring and diagnosis for rotor dynamic system has become current research hot-topics [1-4].

At first, efforts were mainly focused on pattern recognition of faults. And then the performance degradation assessment method was introduced as a new research idea. Compared with pattern recognition of faults, this idea is more concerned on overall performance research of equipment. However fault modes classifying problems are not addressed at depth, which is a novel expansion of existing fault diagnosis techniques. Some performance degradation assessment methods have been reported in recent years, such as logistic regression [5], self-organizing map and back propagation neural network method [6], multiscale morphology analysis [7], support vector machine [8] and entropy-based method [9]. Run-up and shutdown processes of rotating machinery are transient processes which are dynamic modes. The so-called dynamic mode refers to the mode that the characteristic parameters describing the system behavior are not constants but change over time [10]. The main characteristics of rotating machinery in run-up and shutdown processes are various with the vibration features and spectral components, especially near the resonance region.

For solving the difficult problem of assessing the performance degradation, this paper proposes a performance degradation assessment method based on multi-observation Hidden Markov Model (HMM) [11-13]. This method can reflect the change of degradation performance for rotating machinery effectively. A simulated degradation process obtained by decreasing the stiffness of crack rotor dynamic model is used to validate the feasibility of this method.

2. Basic Theory and Algorithm Concerning HMM

2.1. Definition of HMM

The Markov model has been widely applied in natural science and engineering techniques. And its original model is the Markov chain. Practical problems are usually more complicated than the Markov model can describe, since the observed events are not one-to-one correspondence with states, but rather are linked by a set of observation probability distributions, such a model is called the HMM. A HMM can be described by the following parameters.

1) N: the number of states of a Markov chain in a model. The N-state value is $\Theta = \{\theta_1, \theta_2, \dots, \theta_N\}$ and the state at time t of the Markov chain is q_t. Obviously we can get $q_t \in \{\theta_1, \theta_2, \dots, \theta_N\}$.

2) M: the number of observations of a state. The M observation values are $v_1, v_2, \dots, v_N$, and the observation value at time t is o_t, then $o_t \in \{v_1, v_2, \dots, v_N\}$.

3) π: the initial probability distribution vector. $\pi = \{\pi_1, \pi_2, ..., \pi_N\}$, where $\pi_i = P(q_i = \theta_i), 1 \le i \le N$.

4) A: the state transition probability matrix. $A = (a_{ij})_{M\times N}$, where

$$a_{ij} = P(q_{t+1} = \theta_j \mid q_t = \theta_i), 1 \le i, j \le N.$$

5) B: the observation probability matrix. $B = (b_{jk})_{N\times M}$, where

$$b_{jk} = P(o_t = v_k \mid q_t = \theta_i), 1 \le j \le N, 1 \le k \le M.$$

Thereafter, a HMM is denoted as $\lambda = (N, M, \pi, A, B)$ or briefly given as $\lambda = (\pi, A, B)$ in this paper. The HMM can be divided into two parts: one is a Markov chain, described by π and A, whose output is the state sequence, and the other is a random process, described by B, which generates the observation sequence.

2.2. Algrithm Improvement of Multi-Observation Sequence Samples HMM

For rotating machinery performance degradation assessment, condition monitoring data usually have a certain dynamic range. Therefore, in order that the trained HMM can be applied in practice, common features of different monitoring data must be taken into account. Multiple training data sets are required to complete the training of the HMM. This problem can be expressed as follows.

The model $\lambda = (\pi, A, B)$ is trained with the training dataset D_A, where λ reflects the characteristics of D_A. If another dataset D_B is added to the above training process, the characteristics of D_B are also expected to be included in the model through a certain processing.

For rotating machinery performance degradation assessment, D_A and D_B are two samples under the same experimental conditions. Multi-observation sequences are used to train the HMM, and the model parameters are better revaluated. The resulting model can demonstrate equipment operating status more realistically, and the influence of measurement errors on performance degradation assessment can be reduced. Therefore, if enough training data sets are used in the training process, more reliable model parameters will be resulted. For the run-up and shutdown processes of rotating machinery, in order to train the HMM of a degenerative state, multiple run-up and shutdown processes are required to get enough samples.

The standard HMM algorithm can only be used for training of a single observation sequence and many problems may come out if single observation sequence training algorithm is used directly to train multi-observation sequence model. Therefore, improvement of the standard HMM algorithm is needed for multiple observation sequences [14].

It is assumed that there are L observation sequences set $O=\{O^{(l)},\dots,O^{(L)}\}$, and each observation sequence $O^{(l)}=\{O_1^{(l)},\dots,O_T^{(l)}\}$ is independent of the other observation sequences. The standard HMM parameters estimation algorithm revaluation are revised as follows.

$$\bar{a}_{ij}=\frac{\sum_{i=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_{i-1}}\alpha_t^{(l)}(i)a_{ij}b_j\left(O_{t+1}^{(l)}\right)\beta_{t+1}^{l}(i)\right]}{\sum_{i=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_{i-1}}\alpha_t^{(l)}(i)\beta_{t+1}^{l}(i)\right]}, \quad (1)$$

$$\bar{b}_{ij}=\frac{\sum_{i=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l}\alpha_t^{(l)}(j)\beta_{t+1}^{l}(j)\right]}{\sum_{i=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_{i-1}}\alpha_t^{(l)}(j)\beta_t^{l}(j)\right]}, \quad (2)$$

The improved standard HMM parameter estimation algorithm is as follows. Firstly, initial model parameters, π_i, a_{ij} and b_{jk} are calculated based on multi-observation sequences $O=\{O^{(l)},\dots,O^{(L)}\}$, the initial model $\lambda_0=(\pi,A_0,B_0)$, and then $\alpha_t^{(l)}(i)$, $\beta_t^{l}(i)$ are acquired by forward and backward algorithms. Secondly, the improved standard HMM parameter revaluation formula is used to calculate the new model parameters $\overline{\pi_i}$, $\overline{a_{ij}}$ and $\overline{b_{jk}}$ and the initial parameters are substituted by the new ones. The above process is repeated until $P(O/\lambda)$ gets the maximum and if convergence conditions are satisfied, and the model $\bar{\lambda}$ is the best one.

3. Proposed Method for Rotating Machinery Performance Degradation Assessing

If there is potential degradation in rotating machinery, it can be detected through the run-up and shutdown process, and appropriate measures are taken to guaranty safe and reliable operation of equipments.

Run-up and shutdown processes of rotating machinery are transient processes. The model of different degradation levels is established based on the characteristic parameters of different degradation levels [15, 16]. Then the data to be assessed is put into a number of known states HMMs, and the model state which has the largest similar probabilities is the current degraded condition to be assessed [14]. This paper proposes the multi-observation sequences HMM method for the rotating machinery run-up and shutdown processes performance degradation assessment, as shown in Fig. 1.

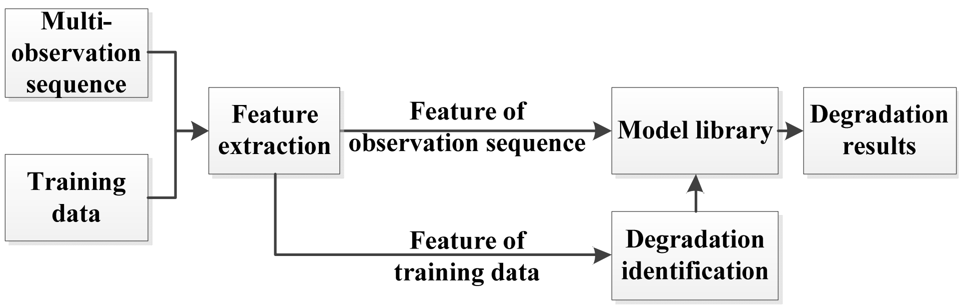


Fig. 1. Degradation assessment flow chart based on the multi-observation sequences HMM.

4. Simulation Analysis of Cracked Rotor Performance Degradation

A cracked rotor in rotating machinery can cause a broken shaft in incidents. Cracks in rotor rotation are leading to cyclical changes in the rigidity of the rotor, thus giving rise to parameter vibration. Effects of different degrees of stiffness of a cracked rotor are different.

In this paper, a numerical simulation for the dynamic model based on simple hinge cracks of transient response is calculated to different degrees of vibration response.

4.1. Transient Dynamic Model of Cracked Rotor

A de Laval rotor with a disc mass m is supported by a massless elastic shaft of length. Suppose that the crack is located near the disc and the weight is dominant, as Fig. 2 [14].

The dynamic equation of the cracked rotor can be written as the following equation.

$$\begin{bmatrix} m & 0 \\ 0 & m \end{bmatrix}\begin{pmatrix} \ddot{x} \\ \ddot{y} \end{pmatrix} + \begin{bmatrix} c & 0 \\ 0 & c \end{bmatrix}\begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} + \begin{pmatrix} x - r_s \cos(\omega t + \alpha) \\ y - r_s \sin(\omega t + \alpha) \end{pmatrix}, \\ = me\omega^2 \begin{pmatrix} \cos(\omega t + \beta) \\ \sin(\omega t + \beta) \end{pmatrix} + \begin{pmatrix} mg \\ 0 \end{pmatrix} \tag{3}$$

where c is the damping coefficient, ω is the angular speed, e is the eccentricity of the disc.

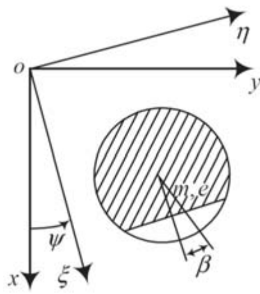


Fig. 2. Cross-section diagram of the cracked rotor.

4.2. Cracked Rotor Simulation Data

Cracked rotor dynamics model, whose stiffness is gradually reduced, is used to verify the rotating machinery performance degradation assessment method based on multi-observation HMM. The stiffness of the rotor is reduced due to cracks, resulting in changes of vibration response in the rotating machinery run-up and shutdown processes. Thus, the response of gradually expanding cracks can be simulated by gradually increasing the relative stiffness decreased coefficient Δ_{k_ξ} in the model rotor. After normalization, $\Delta_{k_\xi} = 0$ means that the stiffness of the rotor does not reduce since there are no cracks and the rotor is in the normal state. While $\Delta_{k_\xi} = 1$ indicates that the rotor's stiffness reduces and the rotor is in the worst state. In the numerical simulation, it is assumed that the rotor starts with an acceleration of $40\ rad/s^2$ and Δ_{k_ξ} was increased from 0 to 1 with a step of 0.01, thus 100 rotor performance degradation conditions were recorded. As for every degradation condition three simulations are showed, the previous two were used for training HMM and then the trained HMM was used to assess the last simulation date set. Due to limited space, only four conditions of the third run are given, as shown in Fig. 3.

The natural frequency of the rotor was assumed as ω_n. Time-domain waveform for rotor with varying degrees of cracking during uniformly accelerated speeding up process is shown in Fig. 3. From Fig. 3, the presence of cracks reduces rotor bending resulting in significantly increased transient response and resonance phenomenon occurs when the rotor speed reaches 1/2 limit speed.

By using the classical Runge-Kutta method, the dynamic response is obtained on the condition that the weight is neglected in order to erase the influence of the static component of the response. Let $a_r = 0.0013$, Ω_0, $\varepsilon = 0.1$, $\Delta_{k_\eta} = 0$, $\beta = 0$, $\zeta = 0.05$.

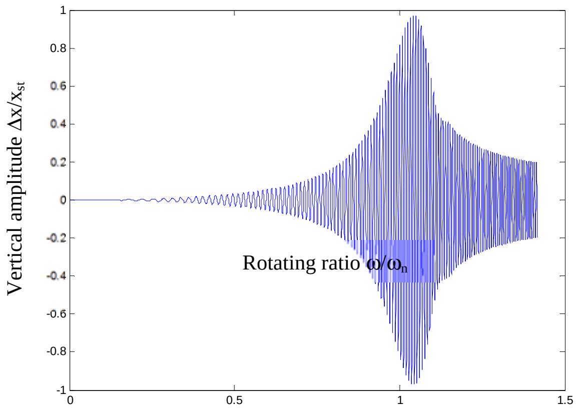


Fig. 3 (a). Transient response of the rotor with varying degrees of cracking during uniformly accelerated speeding up process without cracks.

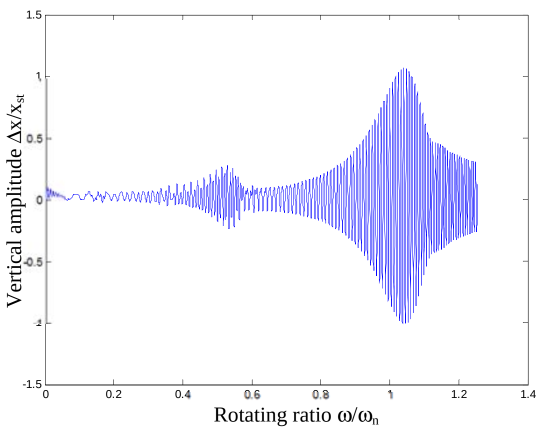


Fig. 3 (b). Transient response of the rotor with varying degrees of cracking during uniformly accelerated speeding up process with $\Delta_{k_\xi} = 0.1$.

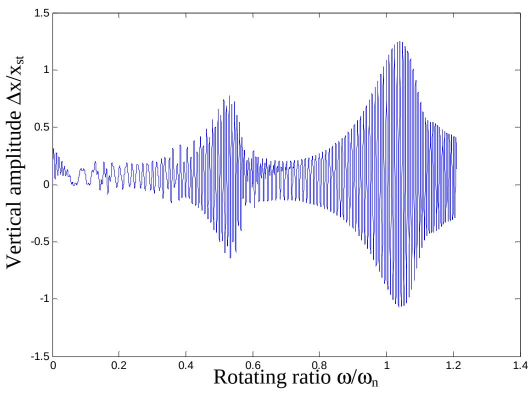


Fig. 3 (c). Transient response of the rotor with varying degrees of cracking during uniformly accelerated speeding up process with $\Delta_{k_\xi} = 0.3$.

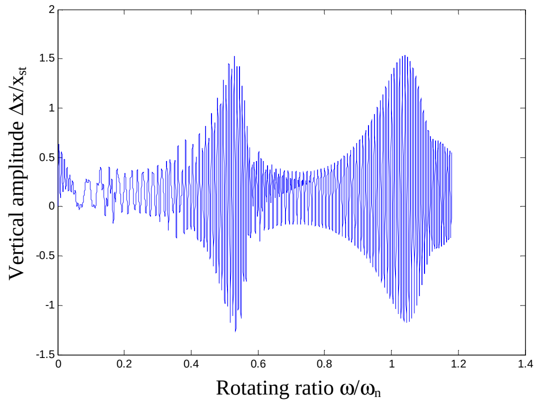


Fig. 3 (d). Transient response of the rotor with varying degrees of cracking during uniformly accelerated speeding up process with $\Delta_{k_\xi} = 0.6$.

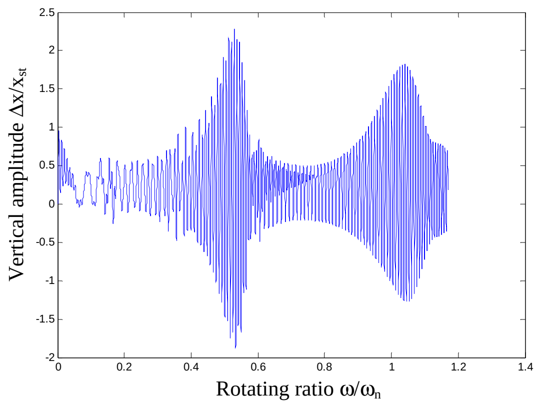
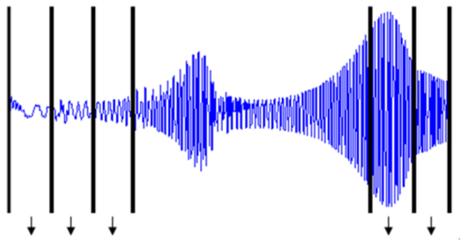


Fig. 3 (e). Transient response of the rotor with varying degrees of cracking during uniformly accelerated speeding up process with $\Delta_{k_\xi} = 0.9$.

Features are extracted from continuous transient vibration signals and scalar quantization is done to meet the discrete data requirement of multi-observation sequences HMM. Signals of the rotor with cracks are equally split to small data sets, root mean square (RMS) parameter are extracted as the feature, and then scalar quantization is done to get the feature observation sequences, which are shown in Fig. 4.



$$O = [O_1, O_2, O_3, \ldots, O_{T-1}, O_T]$$

Fig. 4. Feature observation sequences of the cracked rotor.

In the simulation, every 100 points of the 100 conditions is treated as one segment and 50 feature observation sequences are obtained and input into the HMM for every simulated condition. Normalized RMS and its scalar quantization results are shown in Fig. 5.

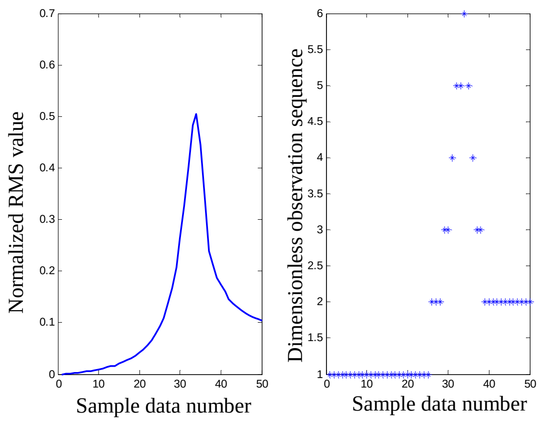


Fig. 5 (a). RMS and response observation sequences for the rotor vibration signals under different operating conditions: rotor without cracks.

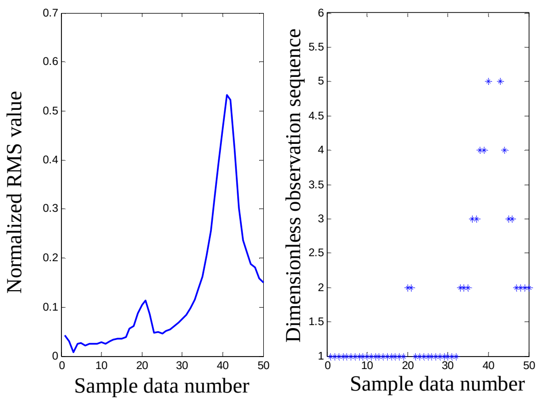


Fig. 5 (b). RMS and response observation sequences for the rotor vibration signals under different operating conditions: rotor with $\Delta_{k_\xi} = 0.1$.

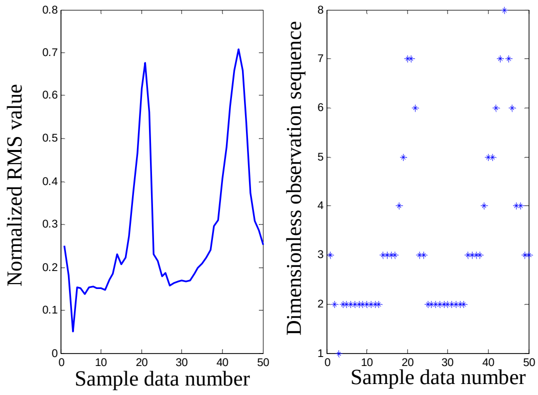


Fig. 5 (c). RMS and response observation sequences for the rotor vibration signals under different operating conditions: rotor with $\Delta_{k_\xi} = 0.1$.

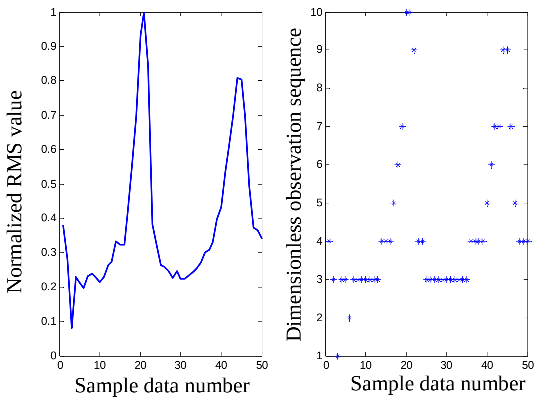


Fig. 5 (d). RMS and response observation sequences for the rotor vibration signals under different operating conditions: rotor with $\Delta_{k_\xi} = 0.9$.

4.3. Performance Degradation Analysis of the Cracked Rotor

It is defined that when the relative stiffness decreased coefficient Δ_{k_ξ} equals to 0.1, 0.3, 0.6 or 0.9, the crack level equals one, two, three or four. Data of four conditions, Δ_{k_ξ} =0.1, 0.3, 0.6 or 0.9, of the first two runs are used to train the model and HMMs of the corresponding performance degradation are acquired. The third simulation sample is used as the test sample and input of the trained HMMs and similar probabilities are compared, the degradation level with HMM outputting the largest similar probabilities is the degradation condition of the rotor. When Δ_{k_ξ} increases, how the crack level changes are shown in Fig. 6.

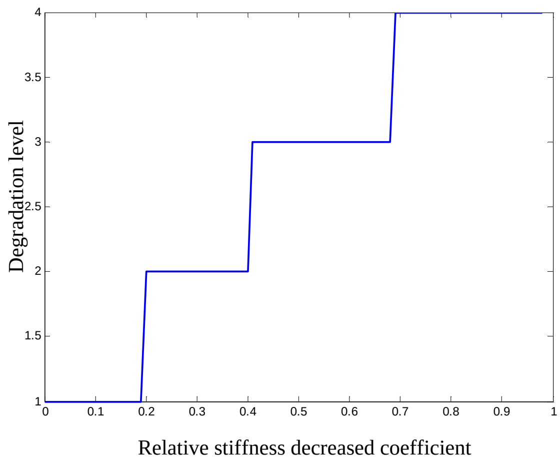


Fig. 6. Crack level identifying curve.

The crack level gradually increases from one to four, this is in accordance with the degradation process of the rotor. Thus, once the samples for different deterioration degrees of equipment are known, its performance degradation can be predicted based on real-time measured signals using this method. The reliability of the equipment will be greatly reduced with the progress of the degradation and the equipment is more prone to failure.

4.4. Results and Discussions

Performance degradation assessment method based on multi-observation sequences HMM for rotating machinery is proposed in this paper. Compared to single observation sequence training [14], the full use of monitoring signals is adapted, and the impact of measurement error is reduced and more reliable evaluation models are attained. Thus current degradation level of rotating machinery can be identified more accurately equipment operation is guaranteed.

5. Conclusions

In this paper, a performance degradation assessment method based on multi-observation sequences HMM for rotating machinery run-up and shutdown processes is proposed. Rotating machinery performance degradation during operation can be effectively assessed by taking advantage of the sensor monitoring signals. Finally, cracked rotor dynamics simulation data with gradually decreasing stiffness was used to verify the feasibility and effectiveness of the proposed method.

Acknowledgment

This research is financially supported by the Beijing Municipal Organization Department Foundation for Excellent Talents of China (2013D009006000003), the National Natural Science Foundation of China (No. 51005015) and the Fundamental Research Funds for the Central Universities of China (No. 2302012FRF-TP-12-161A).

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