International Journal of Smart Home
Vol. 10, No. 7 (2016), pp. 133-142
http://dx.doi.org/10.14257/ijsh.2016.10.7.14

Research on a New Hybrid Intelligent Fault Diagnosis Method and its Application

Zhenhua Wang, Zhentao Liu, Xueyan Lan, Jian Liu, Shaowei Wang, Yangming Wu, Yanbing Xue*

College of Electrical and Information, Dalian Jiaotong University, Dalian 116028, China

Abstract

In order to overcome the shortcomings of slow convergence speed and easy falling into the local minimum values of the BP neural network, an improved particle swarm optimization(PSO) algorithm is proposed to optimize the redial basic function (RBF) neural network, in order to propose a new hybrid intelligent fault diagnosis(IMPSO-RBFNN) method. In the IMPSO-RBFNN method, the adaptive dynamic adjusting strategy is used to control the inertia weight of the PSO algorithm in order to an improved particle swarm optimization(IMPSO) algorithm. Then the IMPSO algorithm is selected to optimize the parameters of RBF neural network by encoding the particle and continuous iteration of the IMPSO algorithm in order to obtain the optimal combination values of the parameters of RBF neural network. The optimal combination values are regarded as the values of these parameters of the RBFNN for constructing the final IMPSO-RBFNN method. In order to test the effectiveness of the proposed IMPSO-RBFNN method, the data from bearing data center of CWRU is selected in this paper. The experiment results show that the IMPSO algorithm can effectively optimize the weights of RBFNN, the IMPSO-RBFNN method can accurately realize high precision fault diagnosis of rolling bearing.

***Keywords**: Intelligent fault diagnosis; improved PSO; RBF neural network; optimization; bearing*

1. Introduction

With the development and popularization of the mechanical technology, the motor plays an increasingly important position in the production and life, it is more and more attention in different areas. If the motor takes place the fault in the course of mechanical operation, it will bring great trouble for the operation of the machine[1]. Rolling bearing is an important component in the motor, it takes on high fault rate and is easy to damage. If the fault feature information can be effectively extracted in the early stage of the fault to realize accurate identification of the bearing running state, and timely replace or repair the damage of the bearing, it can effectively avoid the occurrence of cascading faults[2]. This is highly significant to reduce the economic losses.[1]

At this stage, the most common bearing fault diagnosis method is the artificial diagnosis method, but this method needs to diagnose all components of the bearing by professional and technical personnel. This will need to spend a lot of manpower and time, and improve the cost of fault diagnosis. With the development and popularization of intelligent technology, intelligent fault diagnosis method is also widely applied in the different areas. Therefore, intelligent bearing fault diagnosis method has become a hot issue in the field of machinery research, and has been the attention of many experts and scholars. There proposed a lot of intelligent fault diagnosis methods in the recent years.

Yanbing Xue is the corresponding author.

ISSN: 1975-4094 IJSH

Yang *et al*.[3] proposed the development of a novel condition monitoring procedure for rolling element bearings which involves a combination of signal processing, signal analysis and artificial intelligence methods. Zhang *et al*.[4] proposed a novel approach for integrated machine fault diagnosis based on localized wavelet packet bases of vibration signals. The best basis is firstly determined according to its classification capability. Data mining is then applied to extract features and local decisions are drawn using Bayesian inference. Yang *et al*.[5] proposed an intelligent fault diagnosis method rolling element bearing based on SVM and fractal dimension for recognizing and predicting the complex non-linear dynamic behavior. Fractal dimension can quantitatively describe the non-linear behavior of vibration signal. Lei *et al*.[6] proposed a new approach to intelligent fault diagnosis based on statistics analysis, an improved distance evaluation technique and adaptive neuro-fuzzy inference system (ANFIS). The proposed approach is applied to fault diagnosis of rolling element bearings, and testing results show that the proposed approach can reliably recognize different fault categories and severities. Lei *et al*.[7] proposed a novel hybrid intelligent diagnosis method based on the empirical mode decomposition method, eight intrinsic mode functions (IMFs) and adaptive neurofuzzy inference system to accurately diagnose compound faults of locomotive roller bearings. Lei *et al*.[8] proposed a new method for intelligent fault diagnosis of rotating machinery based on wavelet packet transform (WPT), empirical mode decomposition (EMD), dimensionless parameters, a distance evaluation technique and radial basis function (RBF) network to slight rub fault diagnosis of a heavy oil catalytic cracking unit. Bellini *et al*.[9] proposed a diagnostic techniques for electrical machines with special reference to induction machines. Xu etal.[10] proposed a novel intelligent diagnosis method based on multiple domain features, modified distance discrimination technique and improved fuzzy ARTMAP (IFAM). The proposed method is applied to the fault diagnosis of rolling element bearing, and the test results show that the IFAM identify the fault categories of rolling element bearing more accurately and has a better diagnosis performance compared to the FAM. Mollazade *et al*.[11] proposed a fault diagnosis method based on a fuzzy inference system (FIS) in combination with decision trees. Experiments were conducted on an external gear hydraulic pump. Wang and Chen[12] proposed an intelligent diagnosis method based on the basis of possibility theory and a fuzzy neural network with frequency-domain features of vibration signals for a rolling element bearing. Practical examples of diagnosis for a bearing used in a centrifugal blower are given to show that bearing faults can be precisely identified by the proposed method. Kankar *et al*.[13] proposed a fault diagnosis of ball bearings having localized defects (spalls) on the various bearing components using wavelet-based feature extraction. Li *et al*.[14] proposed an intelligent diagnosis method for condition diagnosis of rotating machinery by using wavelet transform (WT) and ant colony optimization (ACO), in order to detect faults and distinguish fault types at an early stage. Shi [15] proposed an application of support vector machine(SVM) and particle swarm optimization(PSO) to fault diagnosis. the proposed PSO-SVM model is applied to diagnosis operation of rolling bearing failure in this paper, in which PSO is used to determine free parameters of SVM. Zhu *et al*.[16] proposed the wrapper feature selection algorithm by combining the kernel method and neighborhood rough sets to self-adaptively select sensitive features. The combination effectively solves the shortcomings in selecting the neighborhood value in the previous application process. Dou *et al*.[17] proposed a new method for intelligent fault identification of rotating machinery based on the empirical mode decomposition (EMD), dimensionless parameters, fault decision table (FDT), MLEM2 rule induction algorithm and improved rule matching strategy (IRMS) to better equip with a non-expert to carry out the diagnosis operations. Lee and Seo[18] proposed a hybrid multi-class support vector machines (SVMs) and case-based reasoning approach for intelligent fault diagnosis. Cong *et al*.[19] proposed a rolling bearing fault model based on the dynamic load analysis of a rotor-bearing system. The experiments given in the paper have successfully verified the proposed signal model simulation results. Soualhi *et al*.[20] proposed a new approach for fault detection and diagnosis of IMs using signal-based method. The proposed approach is tested on a squirrel-cage IM of 5.5 kW in order to detect broken rotor bars and bearing failure at different load levels. Khajavi and Keshtan[21] proposed a diagnosis and classification of bearing faults using Neural Networks (NN), employing nondestructive tests. Pandya *et al*.[22] proposed a fault diagnosis of rolling element bearing by using multinomial logistic regression and wavelet packet transform. Jiang *et al*.[23] proposed an intelligent fault diagnosis method based on Marginal Fisher analysis (MFA) for rolling bearings. The diagnosis results validate the feasibility and effectiveness of the proposed fault diagnosis method, compared with the other three similar approaches. Zhang *et al*.[24] proposed a novel intelligent fault diagnosis method with multivariable ensemble-based incremental support vector machine (MEISVM), which is testified on a benchmark of roller bearing experiment in comparison with other methods. Zhang *et al*.[25] proposed a novel fault diagnosis strategy based on rotor dynamics and computational intelligence in order to automatically achieve accurate diagnosis for rotating machinery. Wang *et al*.[26] proposed an automatic diagnostic scheme without manual feature extraction or signal pre-processing. Shi and Liang[27] proposed an intelligent oscillatory behavior based signal decomposition (OBSD) method for bearing fault diagnosis. The OBSD technique exploits both the signal separation capability of morphological component analysis (MCA) and the basis creation potential of tunable Q-factor wavelet transform (TQWT).

Particle swarm optimization (PSO) algorithm was originally designed and developed by simulating the social behavior. The PSO algorithm works by attracting the particles in order to search space positions of the high fitness. It has the advantages with simple structure, easy implementation, fast convergence speed and global searching ability, and it does not need to adjust too many parameters. RBF neural network is one of the most popular tools. But the parameters of the RBFNN model have a great effect on the performance. So an improved PSO algorithm based on adaptive dynamic adjusting strategy is proposed to optimize the parameters of the RBFNN model in order to obtain the optimal values of parameter combination. The optimal RBFNN (IMPSO-RBFNN) model is used to diagnose the bearing fault of motor.

The rest of this paper is organized as follows. Section 2 briefly introduces the RBF neural network. Section 3 briefly introduces particle swarm optimization(PSO) algorithm and improved PSO algorithm. Section 4 presents a fault diagnosis(IMPSO-RBFNN-FD) method based on the IMPSO-RBFNN for rolling bearing. Section 5 applies the IMPSO-RBFNN-FD to diagnose the bearing fault diagnosis of motor. Finally, the conclusions are discussed in Section 6.

2. RBF Neural Network

Artificial neural network(ANN) is a new artificial intelligence technology, which is composed of a large number of nerve cells. It offers the significant support for organizing, classifying, and summarizing data. It takes on a high accuracy, adaptability, robustness, effectiveness, and efficiency for fault diagnosis. The ANN usually consists of the input layer, hidden layer and output layer. The input layer is represented by circles and behaves as a buffer. Each neuron receives multiple inputs from other neurons, generates a single output according to the activation function. The activation function can be linear or nonlinear form depending on applications.

The training speed and real-time of the network are considered, the ANN is more adaptable to fault diagnosis. Because BP neural network has some deficiencies of slow learning speed, easy falling into local infinitesimal value, so RBF neural network (RBFNN) is selected to realize the fault diagnosis. The RBFNN belongs to multi-layer forward neural networks, and is composed of the three parts respectively called as input layer, hidden layer and output layer, shown in Figure 1.

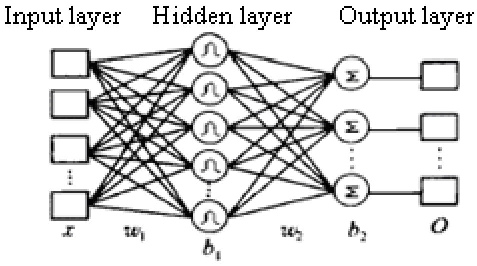

Figure 1. RBF Neural Network

where the input learning vector of the RBFNN is $x = \{x_1, x_2, ..., x_n\}$, $T \in R^n$, the output of the neuron k in output layer can be given:

$$f(x) = \sum_{i=1}^{m} w_i \phi(x, c_i) \tag{1}$$

where x is n-dimension input vector; $\phi(x, c_i)$ is basis function. $f(x)$ is output vector; ϕ is radial basis function; c_i is the centre of the i^{th} basis function with the same dimensions x; $w = \{w_1, w_2, ..., w_m\}$ $T \in R^m$ is output weight matrix; m is the number of the neuron in the input layer, n is the number of the neuron in the hidden layer and k is the number of the neuron in the output layer. Gauss function is acted as basis function, then:

$$\phi(x, c_i) = \exp\left(\frac{-\| \mathrm{x - c_i} \|^2}{2\sigma_i^2}\right) \tag{2}$$

where σ_i is the variance of Gauss samples. The key problem of the RBFNN is to confirm the number of hidden nodes and the locations and width of corresponding center nodes. If these parameters are confirmed, the RBFNN will become linear equations from the input layer to the output layer.

3. Improved Particle Swarm Optimization (PSO) Algorithm

3.1. Particle Swarm Optimization (PSO) Algorithm

Particle swarm optimization (PSO) algorithm was originally designed and developed by simulating the social behavior. The PSO algorithm is a population-based search algorithm. It consists of many individuals, each individual has one position and one velocity. In the PSO algorithm, each particle has a memory function and adjusts its trajectory according to the best visited position and the global best position in the population. The position of best fitness value visited by the swarm is called the global best ($Gbest$) and the position of best fitness value by individual is called the local best ($Pbest$). In the population, the velocity of the particle i is represented as $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})^T$ and the position of the particle i is described as $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})^T$. The velocity and position are updated by following the expressions:

$$v_{ij}(t+1) = vw_{ij}(t) + c_1 r_1 \left(Pbest_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(Gbest_{ij}(t) - x_{ij}(t)\right) \tag{3}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{4}$$

where $v_{ij}(t+1)$ is the velocity of the particle i at iterations j, $x_{ij}(t+1)$ is the position of the particle i at iterations j. w is the inertia weight coefficient, c_1 and c_2 are acceleration coefficients. r_1 and r_2 are random numbers in [0,1].

The basic flow of the PSO algorithm is shown in Figure 2.

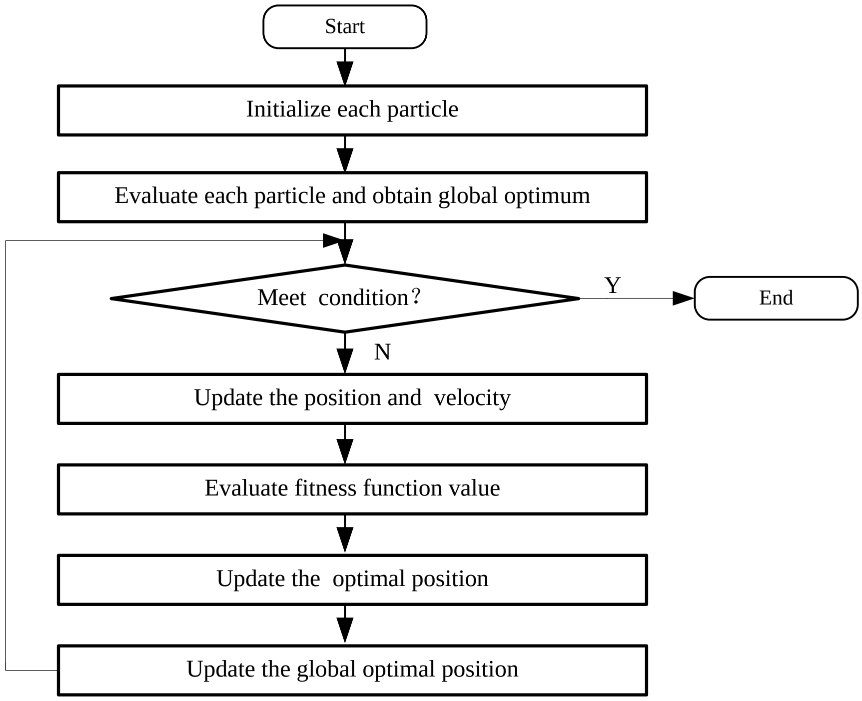

Figure 2. The Basic Flow of the PSO Algorithm

3.2. Improved PSO Algorithm

The value of the inertia weight w will seriously affect the optimization performance of the PSO algorithm. In general, the value of inertia weight w is bigger in the early search in order to guarantee the population search with larger search space and improve the convergence accuracy. The linear decreasing weight method is used to adjust the inertia weight w, it is described as follow:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}} \times t \tag{5}$$

where $w_{\max}$ is the maximum value and $w_{\min}$ is minimum value. $T_{\max}$ is the maximum number of iteration and t is the current number of iteration.

But in the actual application, the search process is a non-linear in the PSO algorithm, the dynamic changes of particles are complex. The linear decreasing weight can not better reflect the actual search process, which will result in the slow convergence speed and convergence precision. So an adaptive dynamic adjusting strategy is proposed to control the inertia weight w for maintaining the diversity of population and reducing the probability of falling into the local optimum. The adaptive dynamic adjusting strategy is described:

$$w = \begin{cases} w_{\max} - \dfrac{w_{\max} - w_{\min}}{T_{\max}} \times t & f \ge f_{avg} \\ w_{\min} + (w_{\max} - w_{\min}) \times \dfrac{f_{avg} - 2 f_{\min}}{2(f - f_{\min})} & \dfrac{f_{avg}}{2} \le f < f_{avg} \\ w_{\min} + \dfrac{w_{\max} - w_{\min}}{T_{\max}} \times t & f < \dfrac{f_{avg}}{2} \end{cases} \quad (6)$$

where f is current fitness value of the particle, $f_{\min}$ is global minimum fitness value of the particle, f_{avg} is global current average fitness value. This strategy makes full use of the current information and historical information to control the updating speed, better reduce the probability of falling into local optimum in the PSO algorithm.

4. A New Hybrid Intelligent Fault Diagnosis Method

There proposed a lot of various fault diagnosis methods in the past decades, such as artificial neural networks (ANN), expert system (ES), rough set theory (RST), fuzzy theory(FT), genetic algorithm (GA), particle swarm optimization(PSO) algorithm, and other new algorithms. These fault diagnosis methods can better realize the fault diagnosis for small-scale objectives in the different areas, but each method takes on its insufficient in the course of diagnosing the fault. Particle swarm optimization(PSO) algorithm is a typical swarm intelligence algorithm, which derived from simulating foraging behavior of birds and fish swarm. It is a population-based search algorithm based on the simulation of the social behavior of birds within a flock, and has shown its good performance in many optimization problems. But the value of the inertia weight w will seriously affect the optimization performance of the PSO algorithm. So an adaptive dynamic adjusting strategy is proposed to control the inertia weight w for maintaining the diversity of population and reducing the probability of falling into the local optimum, in order to propose an improved PSO(IMPSO) algorithm, which is used to optimize the parameters and learning rule of RBF neural network. The goal is to provide a new way to optimize the parameters of the RBF neural network in order to obtain an optimized RBF neural network(IMPSO-RBFNN) method.

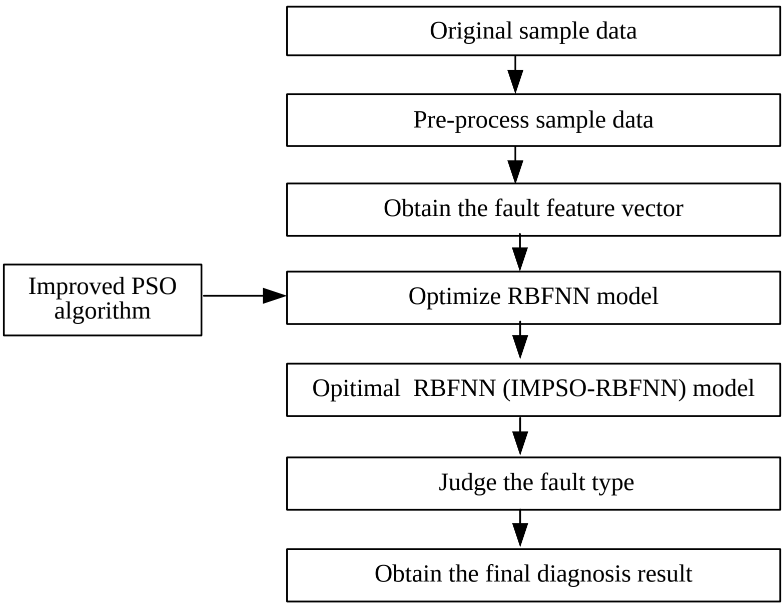

Figure 3. The Framework of the IMPSO-RBFNN-FD Method

The training process of RBF neural network is divided into two steps. The weight w_1 between the input layer and the hidden layer and the weight w_2 between the hidden layer and the output layer are determined. Before the RBF neural network is trained, the numerical value of vector x must be ascertained in order to solve the weight w_1,weight w_2, threshold b_1 and threshold b_2. In the process, the key is to make the number of hidden layer neurons is equal to 1, then the number of the hidden neurons is automatically increased until mean square error meets the precision or the number of neurons to reach the threshold. The new hybrid intelligent fault diagnosis(IMPSO-RBFNN-FD) method based on IMPSO algorithm and RBFNN is shown in Figure 3.

5. Fault Diagnosis Case for Bearing of Motor

In order to test the validity of the IMPSO-RBFNN-FD method, the vibration data is selected from Bearing Data Center of Case Western Reserve University. The deep groove ball bearing of JEM SKF is employed in the experiment. The inner-race fault, outer-race fault and rolling element fault are simulated by grooving on the inner ring, the outer ring and rolling of bearing. The different fault state data are acquired with the 12 kHz sampling frequency. The original vibration signal is divided into the data sample with 4096 points. The vibration signals under three fault states and normal state respectively are 40 samples. In addition, RBFNN-FD and PSO-RBFNN-FD methods are select to compare the fault diagnosis correctness with the proposed IMPSO-RBFNN-FD method.

The environments are: the Pentium CPU 2.40GHz, 4.0GB RAM with the XP operating system, Matlab2010b. Because the initial values of parameters could seriously affect the experiment result, the most reasonable initial values of these parameters are obtained by testing and modifying. The obtained initial values of these parameters are: population size m = 40, max velocity $v_{\max}$ =100, learning factor c_1=2.0 and c_2 =2.0, initial inertia weight w_0 =0.85, r_1 and $r_2 \in [0,1]$, maximum iteration $T_{\max}$ =1000. The experimental simulation results are shown in Table 1.

Table 1. The Experimental Simulation Results for Fault Diagnosis

State	RBFNN-FD	PSO-RBFNN-FD	IMPSO-RBFNN-FD
Normal state	90.34%	96.46%	99.00%
Outer-race fault	89.72%	94.93%	98.64%
Inner-race fault	89.16%	92.34%	95.26%
Rolling element fault	88.64%	91.67%	93.38%

As can be seen from Table 1, by using RBFNN-FD method, PSO-RBFNN-FD method and IMPSO-RBFNN-FD method, the fault diagnosis correctness rate respective are 90.34%, 96.46% and 99.00% for the normal state, 89.72%, 94.93% and 98.64% for outer-race fault, 89.16%, 92.34% and 95.26% for inner-race fault, and 88.64%, 91.67% and 93.38% for rolling element fault. So the proposed IMPSO-RBFNN-FD method can obtain the higher fault diagnosis correctness rate than the RBFNN-FD method and PSO-RBFNN-FD method. It takes on good diagnosis ability for bearing of motor.

6. Conclusion

In this paper, an improved particle swarm optimization algorithm and RBF neural network are integrated in order to propose a new hybrid intelligent fault diagnosis(IMPSO-RBFNN) method. In the IMPSO-RBFNN method, the adaptive dynamic adjusting strategy is used to adjust the inertia weight of the PSO algorithm. Then the IMPSO algorithm is selected to optimize the parameters of RBF neural network by encoding the particle and continuous iteration of the IMPSO algorithm in order to construct the optimal IMPSO-RBFNN method. The deep groove ball bearing of JEM SKF from Bearing Data Center of Case Western Reserve University is used to test the validity of the IMPSO-RBFNN-FD method. The experiment results show that the IMPSO algorithm can effectively optimize the weights of RBFNN, the IMPSO-RBFNN method can obtain the higher fault diagnosis correctness rate for rolling bearing than the RBFNN-FD method and PSO-RBFNN-FD method.

Acknowledgments

This research was supported by the Science and Technology Program of Dazhou (Research on the key technology of intelligent fault diagnosis for spindle system of large and middle NCM), China. The program for the initialization, study, training, and simulation of the proposed algorithm in this article was written with the tool-box of MATLAB 2012b.

References

[1] V. Puig, J. Saludes, J. Quevedo,“Worst-case simulation of discrete linear time-invariant dynamic systems”, Reliable Computing, vol. 9, no. 4 ,(**2003**),pp.251-290.
[2] J. Luo, M. Namburu, K.R. Pattipati, L.Qiao, S. Chigusa,“Model－based and data－driven diagnosis of automotive antilock braking”, IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 40, no. 2 ,(**2010**),pp.321-336.
[3] D.M. Yang, A.F. Stronach, P. MacConnell, J. Penman, “Third-order spectral techniques for the diagnosis of motor bearing condition using artificial neural networks”, Mechanical Systems and Signal Processing, vol.16, no.2-3,(**2002**), pp.391-411.
[4] S. Zhang, J. Mathew, L.Ma, Y. Sun, “Best basis-based intelligent machine fault diagnosis”, Mechanical Systems and Signal Processing, vol.19, no.2,(**2005**) pp.357-370.
[5] J.Y. Yang, Y.Y. Zhang, Y.S. Zhu, “Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension”, Mechanical Systems and Signal Processing, vol.21, no.5,(**2007**), pp.2012-2024.
[6] Y.G. Lei, Z.J. He,Y.Y. Zi, “A new approach to intelligent fault diagnosis of rotating machinery”, Expert Systems with Applications, vol.35, no.4,(**2008**),pp.1593-1600.
[7] Y.G. Lei, Z.J. He,Y.Y. Zi, “Application of a novel hybrid intelligent method to compound fault diagnosis of locomotive roller bearings”,Journal of Vibration and Acoustics, Transactions of the ASME, vol.130, n.3,(**2008**).
[8] Y.G. Lei, Z.J. He,Y.Y. Zi, “Application of an intelligent classification method to mechanical fault diagnosis”, Expert Systems with Applications, vol.36, no.6,(**2009**), pp.9941-9948.
[9] A. Bellini, F. Filippetti, C. Tassoni, G.A. Capolino,“Advances in diagnostic techniques for induction machines”, IEEE Transactions on Industrial Electronics, vol.55, no.12, (**2008**),pp.4109-4126.
[10] Z.B. Xu, J.P. Xuan,T.L. Shi, B. Wu, Y.M. Hu, “A novel fault diagnosis method of bearing based on improved fuzzy ARTMAP and modified distance discriminant technique”,Expert Systems with Applications, vol.36, no.9,(**2009**),pp.11801-11807.
[11] K. Mollazade, H. Ahmadi, M. Omid, R. Alimardani, “An intelligent model based on data mining and fuzzy logic for fault diagnosis of external gear hydraulic pumps”,Insight: Non-Destructive Testing and Condition Monitoring, vol.51, no11, (**2009**), pp.594-600.
[12] H.Q. Wang and P. Chen, “Intelligent diagnosis method for rolling element bearing faults using possibility theory and neural network”, Computers and Industrial Engineering, vol.60, no.4,(**2011**), pp.511-518.
[13] P.K. Kankar, S.C. Sharma, S.P. Harsha, “Rolling element bearing fault diagnosis using wavelet transform”, Neurocomputing, vol.74, no.10,(**2011**), pp.1638-1645.
[14] K. Li, P. Chen, H.Q. Wang, “Intelligent diagnosis method for rotating machinery using wavelet transform and ant colony optimization”, IEEE Sensors Journal, vol.12, no.7,(**2012**),pp.2474-2484.

[15] H.W. Shi, "Particle swarm optimisation-based support vector machine for intelligent fault diagnosis", International Journal of Computer Applications in Technology, vol.44, no.2, (**2012**), pp.159-164.
[16] X.R. Zhu,Y.Y. Zhang, Y.S. Zhu, "Intelligent fault diagnosis of rolling bearing based on kernel neighborhood rough sets and statistical features", Journal of Mechanical Science and Technology, vol.26, no.9,(**2012**),pp.2649-2657.
[17] D.Y. Dou,J.G. Yang, J.T. Liu,Y.K. Zhao, "A rule-based intelligent method for fault diagnosis of rotating machinery", Knowledge-Based Systems, vol.36,(**2012**),pp.1-8.
[18] S.W. Lee and K.K. Seo, "Intelligent fault diagnosis based on a hybrid multi-class support vector machines and case-based reasoning approach", Journal of Computational and Theoretical Nanoscience, vol.10, no.8,(**2013**), pp.1727-1734.
[19] F.Y. Cong, J. Chen, G.M. Dong, M. Pecht, "Vibration model of rolling element bearings in a rotor-bearing system for fault diagnosis",Journal of Sound and Vibration, vol.332, no.8,(**2013**),pp.2081-2097.
[20] A. Soualhi, G. Clerc, H. Razik, "Detection and diagnosis of faults in induction motor using an improved artificial ant clustering technique", IEEE Transactions on Industrial Electronics, vol.60, no.9,(**2013**),pp.4053-4062.
[21] M.N. Khajavi and M.N. Keshtan, "Intelligent fault classification of rolling bearings using neural network and discrete wavelet transform",Journal of Vibroengineering, vol.16, no.2,(**2014**),pp.761-769.
[22] D.H. Pandya, S.H. Upadhyay, S.P. Harsha, "Fault diagnosis of rolling element bearing by using multinomial logistic regression and wavelet packet transform", Soft Computing, vol.18, no.2,(**2014**), pp.255-266.
[23] L. Jiang,T.L. Shi, J.P. Xuan, "Fault diagnosis of rolling bearings based on Marginal Fisher analysis", Journal of Vibration and Control, vol.20, no.3,(**2014**),pp.470-480.
[24] X.L. Zhang, B.J. Wang, X.F. Chen, "Intelligent fault diagnosis of roller bearings with multivariable ensemble-based incremental support vector machine", Knowledge-Based Systems, vol.89,(**2015**), pp.56-85.
[25] J.H. Zhang, W.P. Ma, J.W. Lin, L. Ma, X.J. Jia, "Fault diagnosis approach for rotating machinery based on dynamic model and computational intelligence", Measurement: Journal of the International Measurement Confederation, vol.59, (**2015**), pp.73-87.
[26] X.Q. Wang, H.J. Zhu, T. Rui,Y.F. Li, T.S. Liu, M.X. Liu, "Shift invariant sparse coding ensemble and its application in rolling bearing fault diagnosis", Journal of Vibroengineering, vol.17, no.4, (**2015**), pp.1837-1848.
[27] J.J. Shi and M. Liang, "Intelligent bearing fault signature extraction via iterative oscillatory behavior based signal decomposition (IOBSD)", Expert Systems with Applications, vol.45,(**2016**), pp,40-55.

Authors

Zhenhua Wang, male,born in 1990, College of electrical and information, Dalian Jiaotong University, 2015 graduate students, member of the Chinese electronic society, the main research direction for the development of embedded hardware and fault detection.

Zhentao Liu, male, 2015 graduate students at the school of electrical and information, Dalian Jiaotong University, the main research directions for the development of embedded software and fault detection.

Xueyan Lan, female, College of electrical and information, Dalian Jiaotong University, 2015 graduate students, the main research direction for traffic control intelligent and fault detection.

Jian Liu, male, 2015 graduate students at the school of electrical and information, Dalian Jiaotong University, the main research direction for the traffic information control and communication.

Shaowei Wang, male, 2015 graduate students at the school of electrical and information, Dalian Jiaotong University, the main research direction for the embedded development and control.

Yangming Wu, male, 2015 graduate students at the school of electrical and information, Dalian Jiaotong University, the main research direction for the embedded development and control.

Xue Yanbing, female, born in 1973, Professor of electrical and Information College, Dalian Jiaotong University, Ph.D., master's tutor, the main research direction for the semiconductor gas sensor.