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Early Bearing Fault Diagnosis Based on Improved SFLA and ELM

Network

JINGWEN XU ,Department of Automation, Shanghai Jiao Tong University,
,China;jevonxu@sjtu.edu.cn

YUNXUAN ZHANG , National University of Singapore; Singapore;e0012712@u.nus.edu

ZIQI YIN , Shandong University of Science and Technology, China;ziquyin@outlook.com

ABSTRACT-In this paper, a kind of ELM network based on improved shuffled frog leaping algorithm (CCSFLA) is applied in early fault diagnosis of bearing. Extreme learning machine(ELM)is a new-type single layer forward network. Although the generalization is stronger compared with traditional neural network, random setup of initial parameters increases instability of network. An improved shuffled frog leaping algorithm based on sinusoidal chaotic mapping with infinite collapses and constriction factors(CCSFLA) is proposed in this paper to optimize the ELM and get the CCSFLA-ELM model. Results show that CCSFLA-ELM model is used for optimization and improved the recognition of early fault diagnosis of bearing.

KEY WORDS: chaotic, SFLA ,ELM bearing , fault diagnosis

I. INTRODUCTION

Bearing is a widely used structure in drive system of mechanical equipment. Fault diagnosis of bearing is always an important problem in actual operation of bearing. In industrial environment, bearing vibration signal detected by sensor is always unstable and has complex non-linear relationship in all kinds of fault states. In recent academic researches, intelligent diagnosis method based on morphological wavelet and minimum SVM is proposed aimed at fault recognition of swivel bearing(WU XT,2015 ZHAN JL,2016 JIANG JL,2016).However, the above method expresses local limitation obviously in early bearing fault diagnosis researches.

Extreme learning machine (ELM) is a new-type single layer forward network (SLFN) proposed by scholar Huang GB 2007. It inherits good non-linear mapping capacity of general forward network and overcomes the problem of difficult parameter setting and long training time existing generally in general SLFN with better global convergence. Numerical experiment result shows that the algorithm has good generalization performance.

Swarm intelligence optimization algorithm is a kind of algorithm simulating group activities of social creatures in the nature and modeling to solve parameter estimation in engineering and economy, multi-constraint nonlinear optimization and other problems. In recent researches, swarm optimization algorithm starts to be used in Initial parameter optimization problem of ELM network. For example, in literature (Li B 2010), Li Bin and so on adopt radial based function (RBF) as activation function of ELM and adopt particle optimization algorithm (PSO) and differential evolution (DE) to optimize RMF center and width of hidden nodes in ELM network and improve generalization ability and robustness of RBF - ELM algorithm. Li Dong and so on adopt fruit fly optimization algorithm (FOA) to optimize input weight value and threshold value of hidden layer of ELM neural network, which improves accuracy and stability of algorithm.

Shuffled frog leaping algorithm is a sub-heuristic swarm intelligence algorithm proposed by Eusuff and Lansey in 2003. It has fewer parameters, higher computational efficiency and stronger global searching ability. Although there are no examples using shuffled frog leaping algorithm to optimize ELM network in researches, it has been widely applied to initial parameter optimization of intelligent classification methods such as BP neural network and so on. For example: Zhang Xiaodan and so on propose whisper emotion recognition based on SFLA-BP model in literature (ZHANG XD 2012,ZHANG XD 2013); Qiu Jing proposes researches on short-term gas load prediction model based on improved shuffled frog leaping algorithm and least square support vector machine. However, along with improvement of problem complexity and dimension, convergence rate of shuffled frog leaping algorithm and accuracy of solution are decreased greatly. Therefore, algorithm optimization is of great importance. In previous researches, main duty of these improved frog leaping algorithms is to extend direction and step length of frog leaping to overcome limitation of individual perception and action of frog.

An improved shuffled frog leaping algorithm based on a kind of chaotic map with infinite collapses and constriction factors is proposed in this paper, and improved shuffled frog leaping algorithm is used to optimize initial wight value and threshold value of ELM network. At the same time, ELM network model based on improved shuffled frog leaping algorithm is built and applied to early diagnosis of bearing faults.

II. IMPROVED SHUFFLED FROG LEAPING ALGORITHM(CCSFLA)

A. *Shuffled frog leaping algorithm(SFLA)*

Shuffled frog leaping algorithm (SFLA) is a new-type sub-heuristic swarm intelligence optimization algorithm proposed by Eusuff and Lansey(Ensuff 2006). The algorithm implements thought transfer process according to ethnic classification at the time of simulating frog groups finding foods, and combines global information exchange and local search by cooperation and global information sharing mechanism among interactive frog individuals.SFLA algorithm is mainly divided into global information exchange and local deep search these two parts. Detailed implementation steps of global information exchange and local deep search are as follows:

(I) Global information exchange:

Step1 :Algorithm parameter initialization:

Step2: Initialization of frog group.

Step3: Division of meme group.

Step4:Meme evolution.

Step5: Group shuffle.

(II) Local deep search:

Step1: Expression of generated m_p meme groups is $Y^{i_m} (1 \leq i_m \leq m_p)$ at the time of initialization of algorithm parameters.

Step2: Construction of sub-meme groups.

Step3: Individual update of the worst frog.

Step4: Update of meme group.

Step5: A local deep search shall be finished for a meme group.

Standard SFLA has stronger optimization searching ability and fewer parameters compared with early swarm optimization algorithm.

B. Improved shuffled frog leaping algorithm(CCSFLA)

In order to overcome the defect, chaotic mapping and contraction factors are introduced into algorithm and an improved shuffled frog leaping algorithm that is called CCSFLA (chaotic convergence shuffled frog leaping algorithm) for short is constructed in this paper.

(I) Chaotization of frog individuals

In order to overcome the above defects, a kind of chaotic self-mapping with infinite collapses is introduced in the paper.

Step1: Firstly, random sequence generated by chaotic mapping is used to initialize groups.

Step2: Secondly, in update strategy of the worst frog individual, if adaption $f(U_w)$ of U_w cannot be improved by using "the first two leaps" of local optimum U_b and global optimum U_g , a chaotic individual generated by original individual will be generated to make individuals after update keep away from the worst position quickly.

Through early experimental contrast, sinusoidal chaotic mapping with infinite collapses proposed in literature (He D 2001) is adopted in the paper. Mapping function is as follows:

$$x_{n+1} = \sin(\alpha / x_n) \cdot |x_n| \cdot \varepsilon \quad (1)$$

In the above equation, $\alpha \in (0, \pi)$, value of α determines whether sequence produced by the above mapping has chaotic property. In most literature, value of α is generally $\alpha = 2$. Value problem of the parameter is discussed in this paper.

In chaotic motion of system, *Lyapunov* index is generally adopted to be measuring standard of chaotic state of system. Calculation equation is as follows:

$$l = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \ln \left| \frac{df}{dx} \right|_{x=x_i} \quad (2)$$

Literature (He D 2001) has indicated that λ has better initial value sensitivity, namely when α is fixed, influence of initial value change on chaotic degree of mapping is not so much. When $l < 0$, mapping will converge on a stable fixed point finally. Obtained x_n after sinusoidal mixed degree mapping and variation curve of *Lyapunov* exponent λ with parameter are shown in the Fig.1.

(II) Update strategy with constriction factor

In update strategy of standard SFLA, local optimal frog individual U_b of meme group is firstly used for update in the algorithm, and then global optimal individual U_g of the whole group is used after update is failed. This strategy restricts global information exchange of excellent meme to some extent and improves optimization searching time. In order to make the most of information of U_b and U_g and accelerate convergence time of algorithm, the following improvement for update strategy of the worst individual in standard SFLA algorithm is made referring to particle swarm algorithm based on contraction factors proposed in [16].

$$S = k_1 r_1 (U_b - U_w) + k_2 r_2 (U_g - U_w) \quad (3)$$

$$S = \begin{cases} \min(S, S_{\max}) & S \geq 0 \\ \max(S, -S_{\max}) & S < 0 \end{cases} \quad (4)$$

$$U_w' = h(U_w + S) \quad (5)$$

$$h = \frac{2}{2 - r - \sqrt{p^2 - 4r}}, \rho = k_1 + k_2, p \in [4] \quad (6)$$

In the equation(3), k_1 and k_2 represent given non-negative acceleration constant, r_1 and r_2 represent random number

among $[0,1]$ and h represents contraction factor. Fitness value of U'_w after update of the worst individual and before update are obtained from calculation. If fitness value is improved, U'_w shall be selected for update. If it is not improved, $newU_w = \sin(\alpha/U'_w)$ shall be calculated according to equation (3) to generate new chaotic frog (solution) and implement update.

1. Experimental simulation verification

In order to evaluate performance of CCSFLA algorithm objectively, the following Sphere Function(F1), Griewangk function (F2), Rastrigin function (F3), Ackley function (F4) and so on these 4 typical high-dimensional optimization test functions are introduced in the paper.

Where Sphere function(F1) is a relatively simple unimodal function, while Griewangk(F2), Rastrigin(F3) and Ackley (F4) are complex multi-modal function and distribute extensive local minimum in domain of definition, which increases solution accuracy. Global minimums of 4 above test functions are $F(x)=0$ and are obtained at the time of $x=(0,0,...,0)$.

In the comparative experiment, Setting of increase parameters of CCSFLA is as follows according to related literature (Espinosa AG 2012): $c_1 = c_2 = 2.05$ $k = 0.729$ and independent operation of each function is 20 times. Statistics of mean and variance of optimal solution of independent operations with 20 times.

Mean convergence curves of Sphere and Griewangk are given. Convergence accuracy and convergence speed of the CCSFLA is much higher than that of SFLA. While the expresses mean convergence curves of Rastrigin and Ackley function. It can be known from that in optimization searching of Ackley function, if convergence accuracy is set to be 10^{-13} at the time of aiming at optimization searching problem of high-dimensional complex function, convergence speed of standard SFLA is very slow and will get into local minimum gradually a long with increase of iteration numbers which cannot satisfy accuracy requirement.

Summing up the above experimental data, improved shuffled frog leaping algorithm - CCSFLA proposed in this paper overcomes premature convergence problem of standard SFLA algorithm, expresses good adaptation, stability and global searching ability in high-dimensional optimization searching problems.

III. CCSFLA-ELM NETWORK MODEL

In the Chapter of this paper, the above improved shuffled frog leaping algorithm is matched with ELM neural network to construct a new CCSFLA-ELM network model.

A. ELM network

Extreme learning machine (ELM) is proposed by scholar Huang GB (HUANG GB 2006). It is a single layer forward neural network. Compared with traditional forward neural network, ELM network has better generalization ability, better learning speed and approximation ability. Input weight value and threshold value of hidden layer of ELM network can be given randomly in training.

ELM network structure is show in the following Fig.. Assuming that the network has p neurons of input layer, l neurons of hidden layer, activation function between input layer and hidden layer is $g(wx + b)$ and data sample set is $\{X_i, t_i\}_{i=1}^N$, where $X_i = [x_i^1, x_i^2, \dots, x_i^n]^T$ an N expresses total number of sample set, mathematical model of ELM can be written into:

$$\sum_{j=1}^l b_j g_j(W_j X + b_j) = O_i \quad (i=1, \dots, N) \quad (10)$$

When the forward neural network containing l nodes of hidden layer approaches N samples with zero error, b_j exists. Make

$$f_i(x) = \sum_{j=1}^l b_j g_j(W_j X + b_j) = t_i \quad (i=1, \dots, N) \quad (11)$$

The above equation can be simplified into

$$H\beta = T \quad (12)$$

Learning steps of ELM network are as follows:

Step1: Set a training sample set $\{(X_i, t_i) | X_i \in R^n, t_i \in R^m, i = 1, \dots, N\}$, activation function $g(x)$ and the number l of neuron on hidden-layer.

Step2: Set input weight value W_i and threshold value b_i on hidden layer, $i = 1, \dots, l$

Step3: Calculate output matrix of hidden layer neuron

Step4: Calculate output weight value $\beta = H^+ T$, $T = [t_1, \dots, t_N]^T$ and H^+ is an inverse matrix of generalized Moore of output matrix of hidden layer.

Though advantage of ELM network is outstanding, there is partial defect. Because input weight value and threshold value of ELM network are randomly offered, there may be the fact that matrix sum deviation of partial input weight value is zero, thus partial nodes on hidden layer are ineffective.

B. CCSFLA-ELM network model

An important advantage of this network model is that proper weight value and threshold value can be quickly searched through integrating good global search ability of CCSFLA algorithm and good local search feature of ELM network. Calculation process of CCSFLA-ELM model designed in the research is as follows in this research:

Structure and parameter of ELM neural network can be determined and dimension D of CCSFLA and relation among parameters needing to be optimized in ELM network should be established. Dimension D can be divided into the following four parts according to distribution structure of weight value and threshold value of ELM neural network.

$$D = \underbrace{1, \dots, n_i \times n_h}_{W_{ij}}, \underbrace{1, \dots, n_h \times n_o}_{W_{jk}}, \underbrace{1, \dots, n_h}_{\theta_j}, \underbrace{1, \dots, n_o}_{\theta_k} \quad (13)$$

In above equation, n_i , n_h and n_o respectively represent number of neuron of input layer, neuron of hidden layer and neuron of output layer.

- (1) Rest parameters in CCSFLA algorithm can be determined and frog group can be initialized with chaotic mapping.
- (2) Optimal frog individual (optimal solution) is obtained through searching as initial input weight value and threshold value of hidden layer of ELM network through CCSFLA algorithm.

IV. EARLY BEARING FAULT DIAGNOSIS BASED ON CCSFLA-ELM NETWORK MODEL

In the chapter, above-mentioned methods are used in early bearing fault diagnosis. Normal data of American Case Western University bearing data center is used in the thesis. According to differences of fault point and fault level, vibration signal of bearing is divided into a normal type and 5 typical early fault types in the thesis, which is shown in character as follows: $F = \{F_1, F_2, F_3, F_4, F_5, F_6\}$; where F_1 indicates normal state; F_2 indicates inner ring fault with fault diameter of 0.1778mm; F_3 indicates inner ring fault with fault diameter of 0.3556mm; F_4 indicates ball fault with fault diameter of 0.1778mm; F_5 indicates ball fault with fault diameter of 0.3556mm; F_6 indicates outer ring fault with fault diameter of 0.3556mm. Time domain waveform of them is shown in Fig.2

A. Fault feature extraction based on EMD decomposition and sample entropy

When rolling bearing has fault, obtained vibration signal will have strong non-stable property, irregularity, and complexity. In consideration of obvious limit of traditional time frequency signal processing technology, empirical mode decomposition (EMD) is proposed to be firstly used in the thesis.

It is shown that above-mentioned 6 kinds of typical bearing states can obtain 10 kinds of components after EMD decomposition. As shown in Figures energy of rolling bearing focus on the first five IMF components. Thus, in this research, calculated sample entropies of the first five IMF components are extracted as eigenvalue of each vibration signal sample. 50 samples are extracted for each subcategory, and 300 samples in total. Characteristics extraction of sample is summarized in Table.5

It can be obtained from Table.5 that sample entropy values for IMF signal of normal vibration signals of bearing are both less than types with early existing fault.

B Experimental result

In order to compare advantages and disadvantages of method in the paper, it is respectively subject to BP neural network, ELM network, SFLA-ELM network and CCSFLA-ELM network to analyze early faults of six kinds of bearings.

It can be seen from Table.2 and Table.3 that there is big difference between actual output value and ideal value based on ELM network compared with ideal output value. Especially aimed at test sample of ball damage F_5 , false classification occurs.

And recognition rate based on the three network models and aimed at four bearing states and including 150 test samples is listed in Table.3. From the Table.3, we can know that for rolling bearings that is at normal state (F_1) and that has fault located on outer ring (F_6), the recognition rate of three networks are all over 95% while for mild early damage located on inner ring (F_2) and damage located at outer ring (F_4), the recognition rate of BP network is the lowest which is all less than 80%. Especially for the bearing with fault on the ball, the recognition rate is only 43.60%. This is because BP network will easily run into local optimum when finding the best network' weight and threshold value so that the convergence ability is reduced while compared with network, ELM network is obviously improved in diagnosis-type recognition of all kinds of bearing states. This indicates the excellent global convergence and generalization ability of ELM. Compared with the randomly chosen initial value of parameter, the recognition rate is obviously improved. There into the effect of CCSFLA-ELM is the best and the recognition rate of all kinds of bearing states reaches over 80% and the whole recognition rate is increased by 8.28% and 5.49%.

V. SUMMARY

Based on CCSFLA algorithm, CCSFLA-ELM had more optimal generalization ability and global convergence by utilizing the standard bearing data of American universities to verify the experiment on fault recognition. Compared with standard network, the stability of network was significantly increased and the accuracy of fault recognition was higher. This is a new-type intelligent diagnosis method applicable to the early fault diagnosis of bearing.

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Table.1 lyapunov exponent values with parameter

α	λ	α	λ	α	λ
0.50	-0.2107	2.00	1.6695	5.64	3.0887
1.00	-0.6027	2.50	1.8293	6.00	3.2158
1.50	-2.2881	3.00	2.8034	9.15	3.4342
1.57	-6.5851	4.00	-0.1261	9.30	3.6775

Table.2 Output result based on ELM

State	Actual output					
F ₁	0.9854	0.0131	-0.0120	0.0067	0.0043	0.0080
F ₂	0.0121	0.9867	0.0145	0.0875	0.0345	0.0426
F ₃	0.0236	0.1020	0.9360	0.1104	0.1017	0.3357
F ₄	0.0490	0.0716	0.0156	0.6734	0.0826	0.0568
F ₅	-0.0476	0.4540	-0.0077	0.1384	0.0366	0.0972
F ₆	0.0083	0.4365	-0.1095	-0.0571	0.0172	0.7253

Table.3 Output result based on CCSFLA-ELM

State	Actual output					
F ₁	0.8826	-0.0335	0.0217	0.0601	-0.0350	0.0286
F ₂	0.0175	0.4799	-0.1659	0.1593	0.2583	0.3073
F ₃	-0.0021	0.2646	0.9411	-0.1434	-0.0372	-0.0459
F ₄	0.0035	0.0143	0.0308	0.8171	-0.0717	-0.0230
F ₅	-0.0045	0.2503	-0.0222	0.1535	0.4527	0.0476
F ₆	-0.0012	0.0437	0.0435	0.0458	-0.1573	0.8780

Table.4 Part testing samples ideal output

State	Input					Ideal output
	IMF1	IMF2	IMF3	IMF4	IMF5	
F ₁	1.0137	0.6452	0.4886	0.2329	0.0878	100000
F ₂	1.4565	0.7427	0.6236	0.4343	0.1564	010000
F ₃	1.3178	0.9365	0.6343	0.5455	0.2354	001000
F ₄	1.4375	0.7232	0.5787	0.4672	0.1932	000100
F ₅	1.4797	0.7673	0.6344	0.5452	0.2970	000010
F ₆	1.3236	0.7464	0.6347	0.5738	0.2237	000001

Table.5 Comparison of recognition rate

State	BP (%)	ELM (%)	SFLA-ELM	CCSFLA-ELM
			(%)	(%)
F ₁	100	92.00	100	96.00
F ₂	76.80	82.60	88.00	89.00
F ₃	80.00	83.70	80.00	86.00
F ₄	71.60	81.50	72.00	85.00
F ₅	43.60	62.50	68.00	86.00
F ₆	95.60	90.00	100	99.00
Mean	77.90	81.88	84.67	90.16

FIGURE CAPTIONS

Fig.1 lyapunov exponents curve with parameter α

Fig..2 Time domain waveforms of six kinds of bearing states

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