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FAULT DIAGNOSIS OF ROLLING BEARING BASED ON TKEO-ELM

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Aiming at the issue that the weak vibration signal of early failure in rolling bearing is easily submerged by noise and the time domain feature cannot guarantee the recognition accuracy of the classification model, a fault diagnosis method of rolling bearing based on Teager-Kaiser Energy Operator and Extreme Learning Machine (TKEO-ELM) is proposed. Firstly, the formation mechanism and envelop demodulation will be analyzed. Then, transform the vibration signal from the time domain to Teager-Kaiser domain (TK domain), and extract the TK domain feature to denote local signal characteristics. Finally, establish the classification models of BP neural network, Support Vector Machine and ELM, and compare the performance of classification models using the experimental data of rolling bearing. The experiment results show that the proposed method can ensure the accuracy of classification recognition, decrease the amount of optimized parameters and shorten the optimized time of the model under the same condition.

Keywords: Rolling Bearing, Teager-Kaiser Energy Operator (TKEO), Feature extraction, Back Propagation (BP) Neural Network, Support Vector Machine (SVM), Extreme Learning Machine (ELM).

1. Introduction

Rolling bearing is a common part in rotating machinery which works in high rotate speed and high load situations. So it is one of the most easily damaged parts. Its fault will affect the normal operation of mechanical equipment and lead to a great economic loss or serious accidents. Therefore, the fault diagnosis of rolling bearing is particularly important.

When the bearings run to local damage, its vibration signal of rolling bearing will mutate. However, the salutation of vibration signal generated by the shock of

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damage is weak and it's hard to recognize under a complex noise condition [1]. Therefore, extracting the weak feature of vibration signal from a complex noise condition is a key of the following fault diagnosis. It becomes a focus in fault diagnosis field.

In order to extract the weak feature of vibration signal and realize the fault rolling bearing diagnosis, a great deal of research has been performed by the domestic and overseas researchers. P. K. Kanlar proposed a fault diagnosis method for rolling bearing using the wavelet transform coefficients [2]. N. G. Nikolaou extracted the wavelet transform energy feature as eigenvector to diagnose fault [3]. Yean-Ren Hwang has extracted cepstral coefficient as the input of Artificial Neural Network to diagnose fault [4]. P.K.Kankar have utilized the time domain feature as the input of ANN and SVM to diagnose fault and compared the classification performance of two classification models [5]. Liu has utilized time and frequency feature of intrinsic mode function (IMF) decomposed by Empirical Mode Decomposition (EMD) as the input feature vector of SVM to recognize faults [6]. But these methods still have some limitations, such as the computing scale and complexity of the classification algorithms increases with the number of optimized parameters [7]. Therefore, reducing computation complexity and the number of optimized parameter of classification model also become focus of rolling bearing fault diagnosis. Typically, the research of extracting the fault feature and decreasing the computation complexity has received extensive attention using the envelop demodulation. The Hilbert transform and TKEO have become the most common methods [1, 8-12].

Then, establishing the classification model is also one of the core issues. The classic models include BP neural network, SVM, etc. [13-14]. However, BP neural network has its inherent deficiency, which its convergence rate is slow, easy to fall into the local minimum and sensitive to the selection of learning rate. SVM is a new classification model based on the statistical theory of *VC* dimension and structural risk minimization. In the process of classification, the optimized parameters of kernel function and the penalty factor of misclassification samples greatly increase complexity of the SVM algorithm. Therefore, discovering a learning classification algorithm with high reconstructing accuracy, fast training rate, optimal global result and less optimized parameters is one of hot research issues. Among them, ELM proposed by Huang G.B. [15-16] is a new type of single-hidden layer feedforward neural network. ELM is widely used in the fields of forecasting regression and pattern recognition, because it only needs to generate a connective weight and a threshold value of hidden layer neural between input layer and hidden layer. These parameters don't needs to be adjusted in the progress of training of ELM. At the same time, and the unique optimized result can be obtained only by setting the number of the hidden neuron and decrease the complexity of the ELM classification algorithm [17-21].

The research of ELM mentioned above has many advantages in the aspects of the improvement of generalization ability, the selection of neuron, the accuracy of the regression prediction and pattern recognition. However, the fault diagnosis research of rolling bearing combining TK domain features with ELM are not mentioned in the existing research. Therefore, we should take into full account complex FA-FM signal generated by rolling bearing local fault and highlighting the weak feature of signal using envelop demodulation in this paper. A rolling bearing fault diagnosis method based on TKEO-ELM is proposed. First of all, analyze the formation mechanism of the rolling bearing vibration signal and enveloping feature. Then, transform vibration signal from time domain to TK domain and extract the TK domain feature. Finally, establish the classification models of BP neural network, SVM and ELM and compare the recognition result of classification model by using the rolling bearing experimental data.

The rest of the paper is organized as follows. The background proposing this method is illuminated firstly. The formation mechanism of bearing vibration signal is analyzed in the second part. The basic theories of TKEO, BP neural network, SVM and ELM are discussed in the third part. The realizing process of the method is elaborated in the fourth part. The classification models of BP neural network, SVM and ELM are established and the comparison of the experimental result of the model is described in the fifth part. At last, relevant conclusion and further study are given.

2. Formation mechanism of rolling bearing vibration signal

The rolling bearing failure or malfunctioned will generate a mutational and degenerative shock pulse force in the process of loading and obtain a series of shock pulse with fundamental frequency and a series of high order harmonics. Then, generate high order free damping vibration signal, which is picked up by sensors and circuit resonance. In other words, the vibration signal of sensors is modulated by fault pulse response. Regarding this kind of high order inherent vibration as the carrier of rolling vibration signal, its amplitude will be modulated by external pulse force, which is generated by bearing defects. Thus, the final vibration signal of bearing is a complex amplitude modulated signal. The modulated frequency of modulated wave is the corresponding to the passing frequency of defect. Therefore, the frequency component of modulated wave concludes the corresponding to fault frequency of defect. The inherent mechanism makes it possible to extract the fault feature of rolling bearing using develop modulation and finish the subsequent fault diagnosis using the extracted feature.

3. The explanation of method

a. TKEO demodulation

TKEO is an energy calculation method proposed by Kaiser in 1990 [22]. TKEO detect the modulation components of AM-FM signal by estimating the product of time-varying amplitude and frequency of the signal, and can be regarded as a high resolution energy estimator.

Given a discrete signal $x(n)$, the Teager-Kaiser energy operator $\varphi[x(n)]$ can be defined as:

$$\varphi[x(n)] = [x(n)]^2 - x(n-1)x(n+1) \tag{1}$$

In Eq. (1), the TKEO transform can calculate the energy of signal at any time n only by using three adjacent data samples. Band-pass filter can be disused in TKEO, which can avoid estimating the adaptability of the center frequency and the bandwidth of band-pass filter.

There are four running conditions of rolling bearing in time domain and TK domain analysis results in Figure 1, including normal condition, inner ring fault, outer ring fault and rolling element fault vibration signal respectively (from top to bottom in Fig. 1).

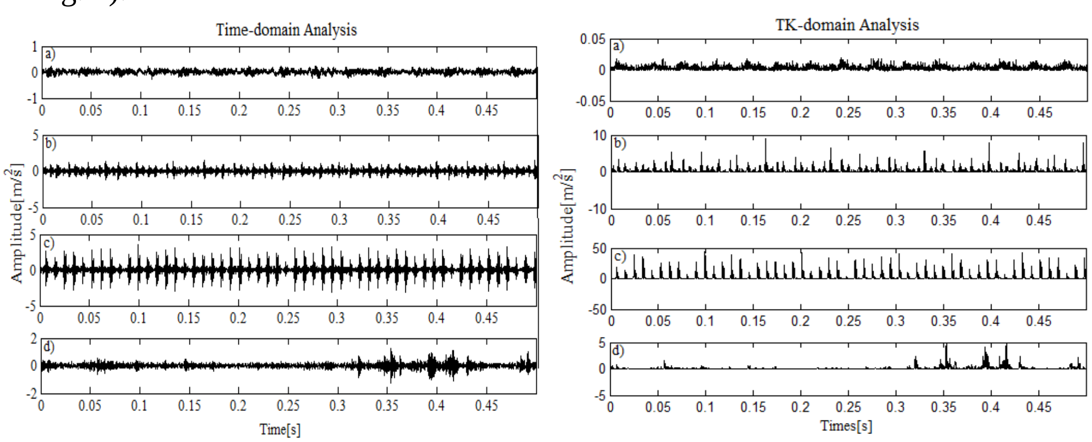

Fig. 1. The time domain and TK domain analysis results

b. BP neural network

BP neural network is proposed by Rumelhard and McClelland in 1986. From the aspect of structure, it is a classical multi-layer feedforward neural network whose transmitting the signal in a forward direction and the back propagation of error are main feature of the network. The fact that the three-layer neural networks with one hidden layer can approach any nonlinear function has been proved in theory [13].

c. SVM

SVM is a new machine learning algorithm proposed by V.Vapnik. The main idea of SVM is to find a hyper plane as the two classes of training samples in order to guarantee the minimum classification error rate for two kinds of classification problems. The basic model of SVM is defined as the largest linear classifier in the interval of feature space. Its learning strategy is interval maximization, which can eventually be transformed into a solution of a convex quadratic programming problem, whose detail is described in [23].

d. Brief Introduction of ELM

We briefly review the ELM, whose detail is described in [15]. The main feature of ELM that distinguishes from conventional neural network learning algorithms is the random generation of hidden nodes. More precisely, the parameters of the hidden nodes are randomly assigned independent of the training samples and the hidden layer output (with L nodes) can be presented by a row vector $h(x) = [h_1(x)$,..., $h_L(x)]$. Given N training samples (x_i, t_i), the mathematical model of the SLFNs is as follows.

$$H\beta = T \tag{2}$$

Where H is the hidden layer output matrix, β is the output weight and T is the target vector.

$$H = \left[h(x_1), \cdots, h(x_N)\right]' \tag{3}$$

In Eq. (3), ‘ $'$ ’ represents matrix transposition. The least square solution with minimal norm is analytically determined using Moore-Penrose generalized inverse $\hat{H}$ [24].

4. The realizing steps of TKEO-ELM

The rolling bearing fault diagnosis method based on TKEO-ELM can strengthen ability of the feature representation by transforming the vibration signal to

TK domain. Then, extract statistic features in TK domain as the input feature vector of ELM classification model. And then we will establish ELM classification model based on the presupposed the link weight ω between input layer and hidden layer and bias b of the neuron of hidden layer randomly. And we can choose S function which is $g(x)=\dfrac{1}{1+e^{-x}}$ as the activation function of ELM hidden layer neuron. Finally, training ELM classification model and testing the effectiveness of method by using the experimental data of rolling bearing with point corrosion fault are described. Meanwhile, compare the classification result of BP neural network and SVM with ELM, and conclude relative conclusions. The realization processes of rolling bearing fault diagnosis based on TKEO-ELM are shown as in Figure 2, and the specific steps described as follows:

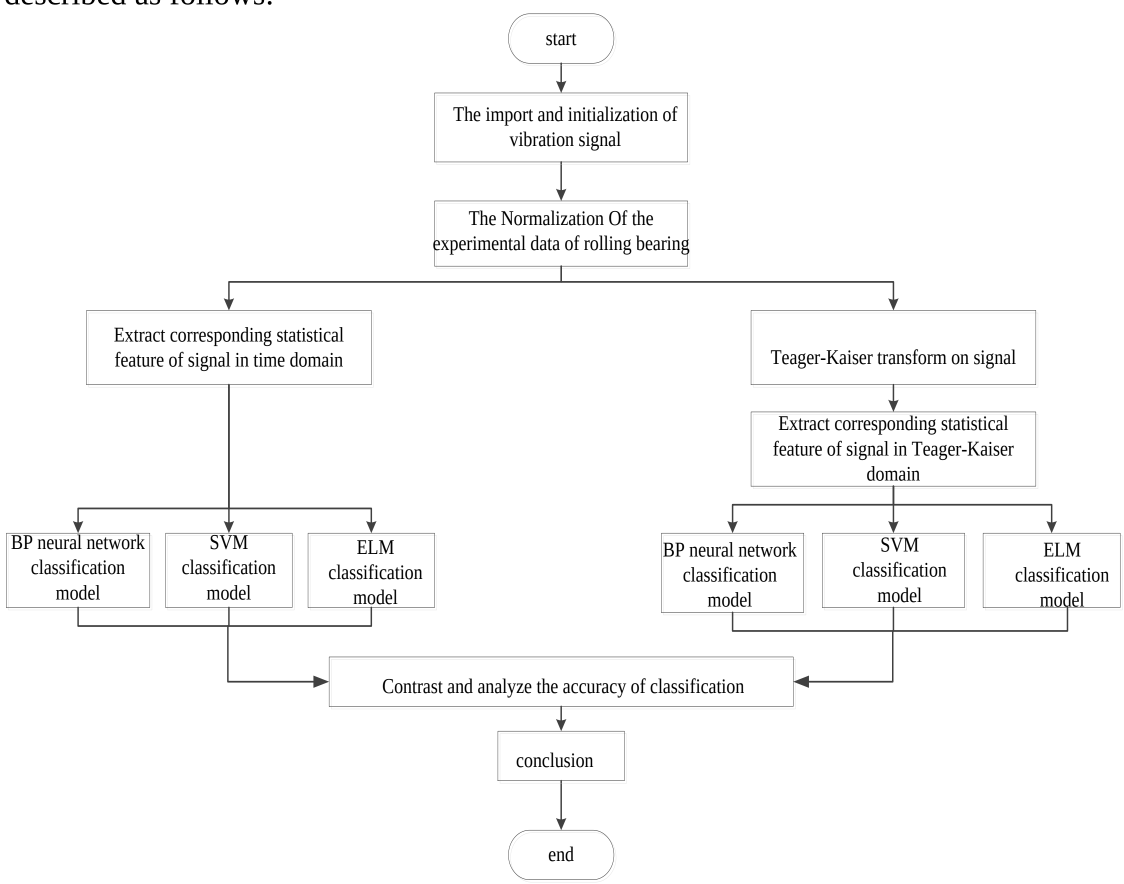

Fig. 2. The realization process of the TKEO-ELM

Step 1: Normalization processing of the experimental data of rolling bearing.
Step 2: Extract 10 statistic features which are the mean value, the peak value, the kurtosis index and energy value in time domain and TK domain.
Step 3: Establish the classification model BP neural network, SVM and ELM, and select 2/3 sample feature randomly to train the network. The remaining features are regarded as the test sample of the classification model.
Step 4: Compare the classification results of classification models in time domain and TK domain and conclude it.

5. Analysis of experimental result

a. Data Resource

In order to verify the effectiveness of the proposed method, the rolling bearing experimental data of Case Western Reserve University in electrical engineering laboratory is used as the test data for validation [25]. Respectively, The vibration acceleration signals (Its measure units is m^2/s) of four different running states, such as the normal state of the bearing, the inner ring fault, the outer ring fault and the rolling element fault, are used for subsequent analysis. The diameter of out ring fault, inner ring fault, and roller fault is 0.007 inches (0.01778 cm). The length of data in each status attribute is 6000. The datum is divided into 400×15 matrix, the data of 4 kinds of status attributes make up 4×400×15 matrix.

b. The feature extraction

The extracted statistic features include mean value, peek value, variance, standard deviation, RMS, crest factor, pulse factor, kurtosis coefficient, fourth-order moment, energy in [26] from time domain and TK domain respectively.

c. The constitute of training sample and testing sample

Aiming to the samples features described in Table 1 and Table 2, 40 attributes of samples (40×40 training sample matrix) are extracted randomly as the input feature vector for BP neural network, SVM and ELM. Samples are correspond to four status labels of bearing (Normal rolling bearing label is 1, inner ring fault label is 2, outer ring fault label is 3, rolling element label is 4) which make up 40×1 training label matrix. The rest of 20 samples (20×20 testing sample matrix) are regarded as testing sample, and its testing label is 20×1 matrix.

d. The analysis and comparison of the experimental result

The comparison of classification accuracy and optimized time of BP neural network, SVM and ELM in time domain and TK domain are shown as Figure 3. The detailed statistic results are shown in Table 1 to Table 3 (In Table, NB represents normal operation situation, BPFI represents inner ring defect, BPFO represents outer ring defect and BSF represents rolling bearing defect). In table 1 to table3, the number in bracket represents the predicted result of classification model. For example, 5(5) of regular state represents 5 samples of rolling bearing regular state, its predicted output state are also 5 regular state, that is to say the recognition result are all right.

By comparing the experimental results in Figure 3 and Table 1 to Table 3, some results are concluded:(1) The experimental results prove that the TK domain features improve the recognition accuracy of the model more effectively than the time domain characteristics. At the same time, the experimental results also show that the model optimization time has increased due to the increase of the TK change process. But compared with BP and SVM, ELM greatly reduces the model optimization time because of less optimization parameters and no iterative optimization. Therefore, the TKEO-ELM method achieves a good balance between classification accuracy and optimization time. (2) The classification result of BP neural network and SVM has little difference, but the optimized time of SVM is longer, which is reason for introducing cross validation algorithm to optimize the parameter of its kernel function and the penalty factor of fault samples in classification results. ELM can achieve the fairly or slightly better performance than BP and SVM, and greatly shorten the optimization time of model under the same conditions. (3)The classification accuracy of TKEO-ELM is higher than BP neural network and SVM. At the same time, comparing with two additional methods, the optimization time of TKEO-ELM is much shorter. In addition, the accuracy of classification model has greatly improved in TK domain, which is attributed to strengthening weak feature of signal by TKEO transform.

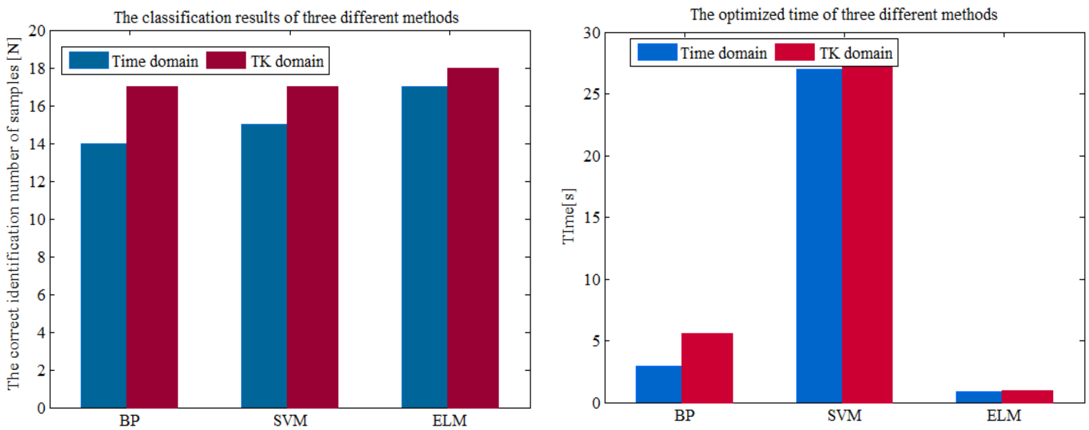

Fig 3. The comparison of classification results

Table 1:

The classification result of BP neural network in time domain and TK domain

The predicted output of classification model		The real state of rolling bearing				Classification accuracy (%)	Optimized time (s)
		NB	BPFI	BPFO	BSF		
Time domain	NB	5(5)	5(0)	5(3)	5(0)	70%	2.920620
	BPFI	5(0)	5(5)	5(0)	5(1)		
	BPFO	5(0)	5(0)	5(0)	5(0)		
	BSF	5(0)	5(0)	5(2)	5(4)		
TK domain	NB	5(5)	5(0)	5(0)	5(0)	85%	5.566291
	BPFI	5(0)	5(5)	5(0)	5(3)		
	BPFO	5(0)	5(0)	5(5)	5(0)		
	BSF	5(0)	5(0)	5(0)	5(2)		

Table 2:

The classification result of SVM in time domain and TK domain

The predicted output of classification model		The real state of rolling bearing				Classification accuracy (%)	Optimized time (s)
		NB	BPFI	BPFO	BSF		
Time domain	NB	5(5)	5(0)	5(0)	5(0)	75%	27.006601
	BPFI	5(0)	5(4)	5(0)	5(4)		
	BPFO	5(0)	5(0)	5(5)	5(0)		
	BSF	5(0)	5(1)	5(0)	5(1)		

TK domain	NB	5(5)	5(0)	5(0)	5(0)	85%	27.352112
	BPFI	5(0)	5(5)	5(0)	5(3)		
	BPFO	5(0)	5(0)	5(5)	5(0)		
	BSF	5(0)	5(0)	5(0)	5(2)		

Table 3:

The classification result of ELM in time domain and TK domain

The predicted output of classification model		**The real state of rolling bearing**				**Classification accuracy (%)**	**Optimized time (s)**
		NB	**BPFI**	**BPFO**	**BSF**		
Time domain	NB	5(5)	5(0)	5(0)	5(1)	85%	0.885231
	BPFI	5(0)	5(5)	5(0)	5(0)		
	BPFO	5(0)	5(0)	5(5)	5(2)		
	BSF	5(0)	5(0)	5(0)	5(2)		
TK domain	NB	5(5)	5(0)	5(0)	5(0)	90%	0.940238
	BPFI	5(0)	5(5)	5(1)	5(1)		
	BPFO	5(0)	5(0)	5(4)	5(0)		
	BSF	5(0)	5(0)	5(0)	5(4)		

6. Conclusions

From the above analysis, the fault diagnosis method of rolling bearing based on TKEO-ELM is efficient to deal with the complex and unstable AM-FM signal generated local defects of rolling bearing. The proposed method can shorten optimized time of model and improved the classification accuracy. Some helpful conclusions are concluded as follows:

(1) It can strengthen weak signal feature by transforming the signal to TK domain using TKEO, which is a convenient and efficient demodulation method.

(2) The parameter of ELM classification model is less than BP neural network and SVM. So, it can shorten the optimized time of the model and guarantee the accuracy of classification under the same conditions.

(3) The TKEO-ELM has combined the advantages of TKEO transform with ELM. Its experimental results indicate that it can be efficient to diagnose the fault of rolling bearing.

(4) Though the experiment of rolling bearing fault diagnosis based on TKEO-ELM has obtained a good result, there is still a lot of research work to be achieved, include

activate function of hidden layer neuron the penalty parameters of sample fault and optimization of ELM classification model.

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