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Fast ICA genetic neural network algorithm

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Abstract: A Fast ICA genetic neural network algorithm is proposed for fault identification in rolling bearings, combining the strengths of backpropagation (BP) and Fast Independent Component Analysis (Fast ICA). The method begins by applying Fast ICA to separate vibration signals into independent components, with each component representing fault-related energy. These energy values form a feature vector. A genetic algorithm then optimizes the initial weights and thresholds of the BP neural network, creating a genetic neural network for improved fault recognition. Experimental results show that this approach enhances the identification of multiple fault types in rolling bearings.

Keywords: Fast ICA, Genetic Neural Network, Fault Identification, Rolling Bearings, Feature Vector

I. Introduction

In practice, the vibration signals measured by sensors are typically mixed signals. To ensure the quality of diagnostic information and improve the accuracy of fault diagnosis, it is necessary to extract independent or relatively independent components from the signals and separate the actual mixed signals. Given the limitations of neural networks, such as large computational requirements, slow speed, and a tendency to fall into local minima, which hinder rapid fault diagnosis and identification of extracted features, a FastICA genetic neural network algorithm is proposed for fault identification. This method combines the advantages of the FastICA algorithm, including fast convergence, low computational complexity, and strong robustness, with the benefits of genetic neural networks, such as fast convergence and the absence of local error jumps. It ensures global convergence during the training process, improves fault identification capability and accuracy, enhances optimization ability, reduces error, and accelerates the speed of bearing fault diagnosis.

II. Feature extraction of vibration signals by FastICA algorithm

Blind Source Separation (BSS) is one of the most commonly used methods for separating mixed signals, with Independent Component Analysis (ICA) being one of the most effective approaches to solving BSS problems [1-4]. The key to applying the ICA algorithm lies in establishing a criterion for measuring the independence of the separation results and corresponding separation methods. This allows for the extraction of individual independent source signals from mixed signals, selecting the appropriate ICA separation method based on the established criterion for measuring the independence of the separation results. Currently, the Fast ICA algorithm is widely used [5-7].

Since each estimated independent component $s(\hat{t})$ contains a certain amount of information, the feature vector extraction is based on the energy characteristics of each estimated independent component $s(\hat{t})$:

1. Perform Fast ICA separation on the original vibration signals of the rotating machinery to select N independent component estimates $s(\hat{t})$ that contain the primary fault information.
2. Calculate the total energy of each independent component $s(\hat{t})$ estimate of the rotating machinery vibration signals:

$$E_i = \int_{-\infty}^{\infty} \left| s_{1ni}\left(\hat{t}\right)\right|^2 dt, i = 1,2,...,N \quad (1)$$

where $s_{1ni}$is the ith independent component.

3. Construct an eigenvector with each independent component estimating the total energy E_i of $s(\hat{t})$ as an element:

$$T = \left[E_1, E_2, E_3, ..., E_N\right] \quad (2)$$

4. The feature vector T is normalized so that $E = (\sum_{i=1}^{N}|E_i|^2)^{1/2}$and the normalized feature vector is:

$$T' = \left[\frac{E_1}{E}, \frac{E_2}{E}, \frac{E_3}{E}, ..., \frac{E_k}{E}, ..., \frac{E_N}{E}\right] \quad (3)$$

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III. Genetic Algorithm Optimization of BP Neural Networks

The BP neural network has several drawbacks, including slow convergence speed, the inability to ensure whether the algorithm converges to the global minimum, and weak optimization capability [8]. This study employs a genetic algorithm to optimize the BP neural network, with the specific optimization process illustrated in Fig. 1.

IV. Genetic Algorithm Optimization of BP Neural Networks

4.1 Principles of the FastICA genetic neural network algorithm

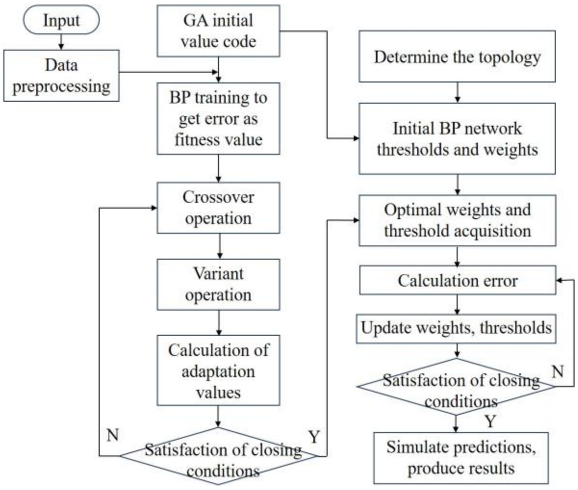

Fig.1 Genetic Algorithm to Optimize BP Network Process

In conjunction with the Fast ICA separation algorithm, this paper proposes a genetic neural network algorithm based on Fast ICA. This method first applies the Fast ICA separation algorithm to estimate the noisy mixed signals $s(t)$, resulting in multiple independent component estimates $s(\hat{t})$ of fully separated source signals. Secondly, a genetic algorithm is utilized to optimize the weights and thresholds of the BP neural network, yielding an optimized BP neural network. Finally, the normalized energy of the multiple independent component estimates $s(\hat{t})$ obtained from the Fast ICA separation of the rotating machinery mixed signals is used as input to the genetic neural network, applied in the training and prediction of the optimized BP network. This method ensures global convergence during the training process, enhancing fault identification capabilities and accuracy. Fig. 2 illustrates the schematic diagram of the Fast ICA genetic neural network algorithm, where e is input variables and Y is output variables.

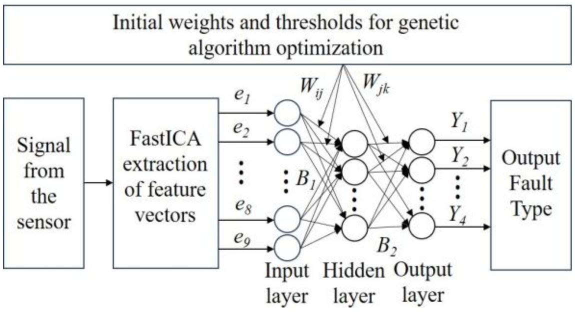

Fig. 2 Principles of Negative Entropy Genetic Neural Network Algorithm

4.2 Bearing fault diagnosis based on FastICA genetic neural network algorithm

The paper collected fault signals from the rolling bearings of a double-suction centrifugal pump. The rolling bearing model is 6312, with a rotational speed of 1,480 r/min. One DH131 piezoelectric accelerometer was installed axially on the rolling bearing, while three DH187 piezoelectric accelerometers were installed radially (one on the top and two on the sides of the rolling bearing).

Table. 1Training samples for faulty bearings

Fault type	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
Normal	0..01377	0.1791	0.0878	0.2142	0.0426	0.0897	0.0851	0.0597	0.0688
Outer ring	0.0994	0.1578	0.1802	0.2470	0.1221	0.0951	0.0506	0.0227	0.0174
Rollers	0.2589	0.2005	0.0487	0.0054	0.0224	0.0065	0.0893	0.2303	0.0862
Inner ring	0.1541	0.2481	0.0824	0.0035	0.0324	0.0334	0.0379	0.0515	0.0906

By extracting certain characteristic values of rolling bearing faults, four fault types–normal bearing, outer race fault, rolling element fault, and inner race fault–were used as training samples for the genetic neural network. Using the Fast Independent Component Analysis (Fast ICA) algorithm, the energy of each estimated independent component, denoted as E, was calculated for a subset of samples. This data was then used as training samples for the genetic neural network, as shown in Tab. 1.

Based on the number of fault types and the genetic neural network, the number of hidden nodes

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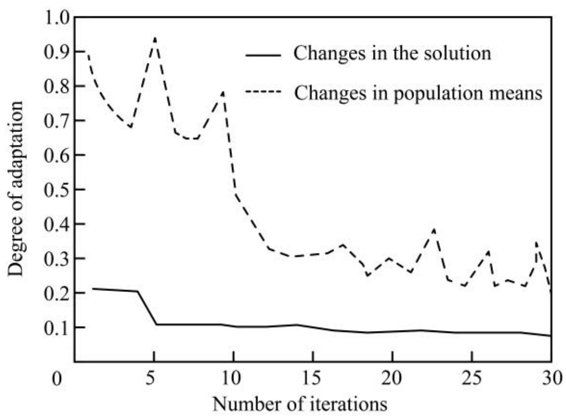
was determined. The structure of the genetic neural network was set as 9-5-4, with the weight and threshold values defined within the range of [−1, 1]. These weights and thresholds were converted to binary to reduce the time required for the genetic algorithm to find the global optimum. The population size for the genetic algorithm was defined as 20, with a maximum of 30 iterations. Fig. 3 illustrates the relationship between the number of iterations of the genetic algorithm and the overall error.

As shown in Figure 3, the genetic algorithm found the global optimum by the 24th generation of the optimization process. Even with further genetic iterations, this value remained unchanged. At this point, the corresponding encoding string can be identified, and the binary codes on the encoding string can be converted to their corresponding decimal values for the neural network weights and thresholds. These weights and thresholds were then used as the initial weights and thresholds for the BP neural network, which was trained using the training samples. The training step was set to 100, with a learning rate of 0.01 and a target training error of 10^{-5}. The training process, as shown in Fig. 4, was completed in just six steps.



The trained network was tested with prediction samples, and the actual network outputs along with the expected outputs are presented in Tab. 2.

As shown in Tab. 2, the actual output values are close to the target output values. For Sample 1, the normal rolling bearing, the actual output value and the target value differ by 0.0013. For Sample 2, with an outer race fault, the difference between the actual output value and the target value is 0.0039. For Sample 3, with a rolling element fault, the actual output value and the target value differ by 0.0013. For Sample 4, with an inner race fault, the actual output value and the target value also differ by 0.0013. The errors between the actual output values and the target values for all samples indicate that the network has a high predictive accuracy. Therefore, the application of the proposed method to rolling bearing fault identification has enhanced its capability, reduced errors, and accelerated the diagnosis speed of rolling bearing faults.

Fig. 3 Relationship between the number of iterations of a genetic algorithm and the overall error

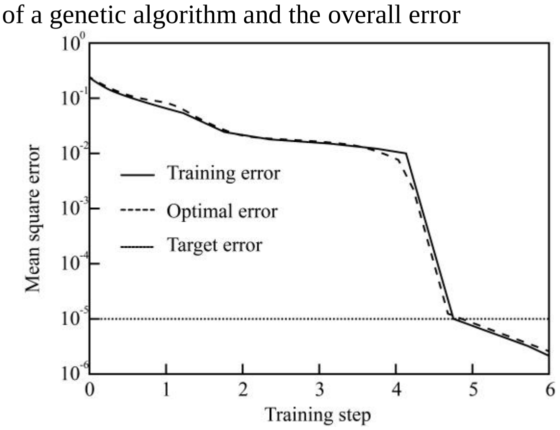


Fig. 4 Training of Genetic Neural Networks

Table 2 Results of the diagnosis

Input	Real output				Target output				Fault type
Sample 1	0.9987	0.0005	0.0005	0.0007	1	0	0	0	Normal
Sample 2	0.0002	0.9961	0.0004	0.0009	0	1	0	0	Outer ring
Sample 3	0.0001	0.0000	0.9987	0.0007	0	0	1	0	Rollers
Sample 4	0.0001	0.0000	0.0002	0.9987	0	0	0	1	Inner ring

V. Conclusions

Using the FastICA-genetic neural network method for fault identification in rolling bearings offers the following advantages: 1) The FastICA separation algorithm is employed for feature extraction from fault signals, offering rapid convergence, low computational complexity, and strong robustness; 2) The genetic neural network exhibits fast convergence and avoids local error trapping, thus overcoming the neural network's tendency to get stuck in local minima, thereby enhancing fault identification capabilities and accuracy; 3) The FastICA-genetic neural network method performs effectively in fault diagnosis of

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rolling bearings, providing a rapid and efficient discriminative approach for bearing fault diagnosis.

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