Research on Model Optimization Method Based on Differential Evolution

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Abstract. Nowadays, industrial upgrading and transformation continues to deepen, based on the deep neural network model of the integration of the advantages of the application is more and more prominent. Rolling bearings can not be ignored as the existence of mechanical equipment. A convolutional neural network parameter optimization algorithm based on differential evolution is proposed. The loss function of the fault diagnosis model is taken as the objective function of the optimization algorithm, and the optimization model is mainly aimed at optimizing the training parameters such as the number of convolutional kernels, convolutional kernel size, and step size of the 3D convolutional neural network, and the optimal parameter setting values are derived. Compared with the pre-optimization fault diagnostic model, the prediction accuracy of the fault diagnostic model is improved by 0.35%, and the loss rate is decreased by 1.13%, and the obtained fault diagnostic model has higher diagnostic accuracy.

Keywords: Machine learning; Fault diagnosis; Convolutional neural network; Differential evolution; Data analysis; Keras.

1. Introduction

The evolutionary principle of survival of the fittest is followed in nature , and the evolution from lower to higher level is accomplished through the operations of transfer, selection and mutation . After research, it is found that the evolutionary principle of survival of the fittest can be modularized to form some optimization algorithms. Nowadays, optimization algorithms based on the principle of biological evolution have been widely used, and evolutionary computational algorithms have been greatly developed. Differential evolutionary algorithm is an emerging evolutionary computing technology [1]. It is also quite effective in dealing with the optimization problems of complex systems. Differential evolution reduces the complexity of evolutionary optimization through simple mutation operations such as differential computation and "one-to-one" survival strategy of competition among individuals of a population. Differential evolutionary algorithms are characterized by strong global convergence ability and robustness, and they can optimize the objective without the help of feature information of the problem to be solved[2, 3]. As an efficient parallel search algorithm, the application of differential evolutionary algorithms is not only limited to the field of mathematical model optimization problems, but also has a wide range of applications in many disciplines. Differential evolutionary algorithms have been applied in many cutting-edge fields, such as artificial neural networks, mechanical design, signal processing, economics and operations research.

2. Bearing Fault Diagnosis Model Based on 3D Convolutional Neural Networks

2.1 3D Convolutional Neural Network Diagnostic Model

2.1.1 3D Convolutional Neural Network Parameterization in Keras Framework

The loss rate and prediction accuracy of the trained 3D convolutional neural network fault diagnosis model are shown in Table 1. The results show that the 3D convolutional neural network has excellent prediction and classification effect on 3D data, and the accuracy of the tester reaches 99.16%.

Table 1. Fault diagnosis model prediction results

Testing Indicators	**Test results**
loss ratio	0.0676
	99.16%

The loss function curve of the 3D convolutional neural network based fault diagnosis model is shown in Figure 1.

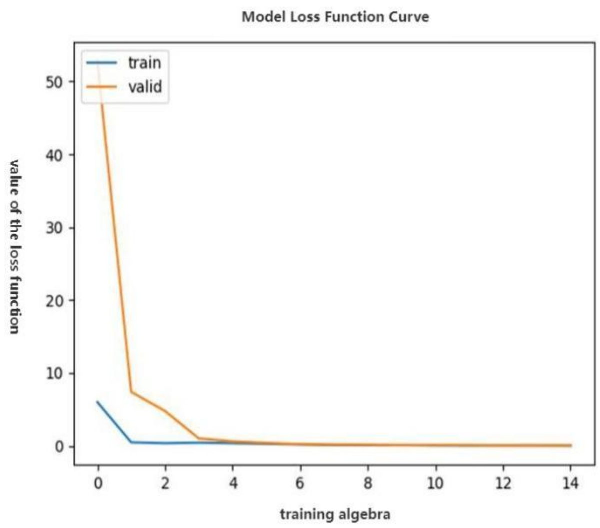

Figure 1. 3D Convolutional Neural Network Fault Diagnosis Model Loss Profiles

3. Differential Evolution

3.1 Differential Evolution Algorithm Flow

Differential evolutionary algorithm adopts the evolutionary strategy of "difference-mutation-selection", the algorithm adopts the real number coding of data, and obtains the difference vectors based on the operation of difference-mutation, and carries out the competitive selection operation of difference vectors and target vectors by using the survival strategy of "one-to-one". The "one-to-one" survival strategy is used to compete for the selection of difference vectors and target vectors[4]. If the maximum number of iterations or termination conditions are not reached, the number of iterations k = k + 1, into the next generation of calculations; if the maximum number of iterations or termination conditions are reached the output of the best individual differential evolutionary algorithm flow is shown in Figure 2.

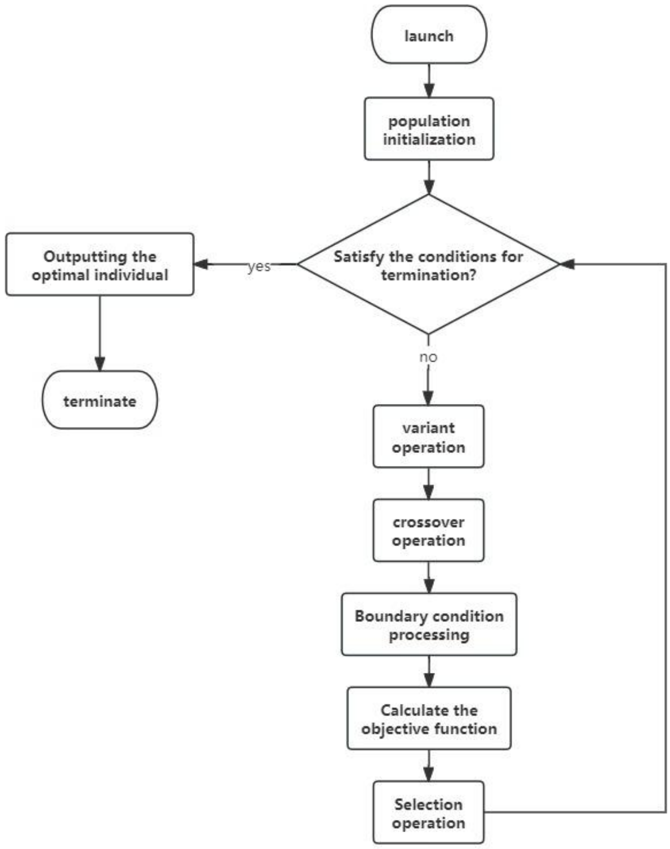

Figure 2. Flowchart of Differential Evolution Algorithm

3.2 Parameters of the differential evolutionary algorithm

The parameter setting values in the differential evolution algorithm will affect the optimization results, and setting more reasonable parameter values is conducive to the rapid convergence of differential evolution to the global optimal solution. The definition and setting of each parameter are shown as follows: (1) Population size The larger the population size set for NP differential evolution, the better the diversity of the population. Larger population size also increases the global optimization seeking ability of differential evolution [5]. (2) Variation operator F In general, the value of the variation operator F ranges from 0 to 2. The value of the variation operator determines the amplification ratio of the differential vector. Usually the variance operator F is set to 0.5 [6]. (3) Crossover operator CR The value of the crossover operator generally ranges from 0 to 1. The crossover operator indicates the probability of the crossover operation occurring in the test vectors. Usually the crossover operator is set to 0.9 or 1.0 [8]. (4) Maximum Evolutionary Algebra G The common termination condition for differential evolution is to set the maximum evolutionary algebra, which is expressed as the differential operation stops when the number of differential evolutionary algebra reaches the maximum evolutionary algebra, and outputs the current population vector. In general, the maximum evolutionary algebra is set between 1--~500. (5) Termination condition Usually, the termination condition of differential evolution is the maximum evolutionary algebra, but according to the characteristics of the objective function, other judgment criteria are also chosen as the termination condition.

3.3 Optimization of fault diagnosis model based on differential evolutionary algorithm

The fault diagnosis optimization model based on differential evolutionary algorithm first needs to determine the parameters to be optimized. According to the characteristics of the differential evolutionary algorithm and the parameter settings based on convolutional neural network, and according to the value of the loss function of the diagnostic model to determine the direction of optimization of differential evolutionary parameters. Its main optimized parameters are shown in Table 2.

Table 2. Differential Evolutionary Optimization Parameters

variable name	**Optimization parameters**	**parameter scale**
X1	Number of convolution kernels in C1	50~100
X2	Number of convolution kernels in C2	50~100
X3	Convolutional kernel size in C1	3x3x3、5x5x5…
X4	Convolutional kernel size in C2	3x3x3、5x5x5…
X5	Convolutional step size in C1	1~5
X6	Convolutional step size in C2	1~5
X7	Convolutional kernel activation function in C1	Sigmoid、tanh、relu
X8	Convolutional kernel activation function in C2	Sigmoid、tanh、relu

After determining the parameters of the convolutional neural network that need to be optimized as well as the scale of the parameters, the parameter optimization model based on differential evolution can be built. Among the key parameters of the optimization model also need to be set, the setting values are shown in Table 3 below

Table 3. Differential Evolution Key Parameter Settings

Key volumes	**parameterization**
Population size NP	20
The probability of variation F	0.5
Cross probability CR	0.8
The number of iterations G	100

After the key parameters of differential evolution are set, the objective function of differential evolution, also known as the fitness function, needs to be set, i.e., the loss function value of the convolutional neural network is used to judge the optimization direction of differential evolution[7].

$$A=f(x_1,x_2,x_3,\cdots,x_8) \tag{1}$$

Equation (5-3) in A that is the value of the loss function of the convolutional neural network, which indicates the loss function value with the change of the neural network parameters of the function, the general choice of cross-entropy as a loss function of the determination, the formula is expressed as:

$$H(\alpha,\beta)=-\sum a(x)\log\beta(x) \tag{2}$$

In Eq. (5-4), H denotes the probability value that the diagnostic model correctly classifies the data, where α denotes the probability distribution of correct label classification and β denotes the probability distribution of incorrect label classification.

4. Comparison of experimental results

According to the scale and characteristics of the parameters to be optimized by the convolutional neural network, the algorithm of discrete difference evolution is chosen to optimize the fault diagnosis model. Through the construction and establishment of the above experimental steps, the discrete differential evolution model is constructed as well as the optimization parameters of the convolutional neural network are determined. The experimental results after differential evolution optimization are shown in Figure 5.2. As shown in the figure discrete differential evolution of the loss curve for the segmented curve, and after the iterative process continues, the objective function value that the loss value continues to decline in the iteration after the completion of the output change curve.

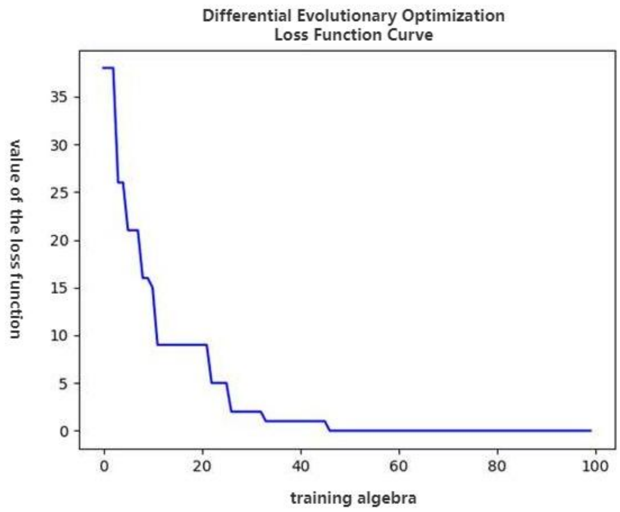

Figure 3. Optimization results of differential evolutionary algorithm

The optimized parameter settings after the completion of the iterations are shown in Table 4 below, where the value of each variable is the value that best fits the objective function after differential evolutionary optimization.

Table 4. Differential Evolutionary Optimization Parameter Results

variable name	Optimization parameters	Optimized parameter results
X1	Number of convolution kernels in C1	128
X2	Number of convolution kernels in C2	64
X3	Convolutional kernel size in C1	3x3x3
X4	Convolutional kernel size in C2	3x3x3
X5	Convolutional step size in C1	5
X6	Convolutional step size in C2	5
X7	Convolutional kernel activation function in C1	Rule
X8	Convolutional kernel activation function in C2	Rule

The prediction accuracy of the convolutional neural network fault diagnosis model after optimization by differential evolution and after training is shown in Table 5.

Table 5. Comparison of results before and after model optimization

Predictive indicators	Prediction accuracy before optimization	Prediction accuracy after optimization

loss ratio	6.76%	5.63%
accuracy	99.16%	99.51%

Compared with the pre-optimization fault diagnosis model, the prediction accuracy is improved by 0.35% and the loss rate is decreased by 1.13%. This shows that the diagnostic accuracy of the fault diagnosis model based on differential evolution optimization is higher. The diagnostic model optimized by differential evolution has certain guiding significance in parameter selection. Parameter optimization can be carried out in the same way in the face of the same problem, so as to provide theoretical basis and mathematical argumentation in the parameter selection of convolutional neural network.

5. Summary

This chapter focuses on the differential evolution optimization algorithm and proposes a 3D convolutional neural network fault diagnosis optimization model based on differential evolution. The optimization model adopts the structure of combining differential evolution optimization algorithm and 3D convolutional neural network, optimizes the 3D convolutional neural network training parameters, and experimentally verifies the feasibility of differential evolution algorithm in the field of optimization machine learning algorithm.

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