Design of an Algorithm of Fault Diagnosis Based on the Multiple Source Vibration Signals

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Abstract. The main application direction of this paper is to diagnose various fault states or normal states of the three kinds of pumps, such as the lubricating oil pump, the centrifugal pump and the hydraulic pump, on the industrial equipment and other equipment. The data processing is performed according to the acceleration signals measured by each sensor in the fault or normal state of the three pumps provided, and the data is divided into a training set and a validation set. The common algorithm of fault diagnosis is adopted, and the one-dimensional convolutional neural network is used as the core to construct the overall framework of fault diagnosis, so as to judge whether the fault is faulty by detecting the single-source vibration signal, and obtain the correct rate of judgment. The two-dimensional convolutional neural network model is first built, and the method of convolutional neural network is used for multi-source information fusion. The vibration signals measured by the acceleration sensors at four different locations are composed of two-dimensional signals and input into the new two-dimensional convolutional neural network. Input the dataset classification into the architecture for architecture training and accuracy analysis, and change the convolutional neural network structure to achieve higher accuracy.

Keywords: Fault diagnosis · Convolutional Neural Network · Multi-source information fusion

1 Introduction

Mechanical fault diagnosis has always been a research hotspot at home and abroad. For a long time, the signal processing methods were used to study the fault types of rotating machinery such as pumps. The specific methods include singular value analysis [1, 2], wavelet transform [3], empirical mode decomposition, etc. There are many machine learning based fault diagnosis methods beyond the limitations of traditional methods, such as K nearest neighbor classification. In recent years, the concept of Convolutional Neural Networks (CNN) [4–8] has been put forward, which has become the most popular fault diagnosis method due to its strong feature extraction ability [9, 10] and the use of deep learning [11]. The aim of this paper is to study whether the pumps of industrial equipment work normally, including oil pumps, centrifugal pumps and hydraulic pumps,

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which are necessary for industrial equipment. By measuring their real-time acceleration signals, it can judge whether the pumps on industrial equipment work normally or fail in time. Normal operation is exactly what we want, but if a fault is detected, stop the operation of the industrial equipment in time, and conduct maintenance in time to prevent the industrial equipment from having very serious consequences after operation.

2 One Dimensional CNN Architecture Design, Data Processing and Optimizer Selection

The preliminary design of the architecture of one-dimensional convolutional neural network is completed, which is a key step for the construction of the overall architecture of the subsequent fault diagnosis algorithm. In addition to the construction of one-dimensional convolutional neural network architecture, attention should also be paid to the input data input into the architecture, that is, the processing of data sets. The processing of data sets is very important, including the classification and labeling of data sets. If the data sets are too few or the samples are unbalanced, special processing should also be carried out on the data sets. As with dataset processing, the choice of optimizer is also important.

The basic structure of one-dimensional convolutional neural network always roughly includes convolution layer, pooling layer, activation function layer, Batch Normalization (BN layer), full connection layer and classification layer. For two discrete signals, the definition of convolution is shown in formula (1).

$$f[n] * g[n] = \sum_{m=-\infty}^{+\infty} f[n]g[n-m] \tag{1}$$

The convolution layer, BN layer, activation function layer and pooling layer are preliminarily selected to form a hidden layer structure. The hidden layer structure appears five times repeatedly to achieve more levels of information extraction. Then through the full connection layer and the classification layer, the probability of nine faults is finally output.

Classification of data sets, that is, data sets are divided into training sets and verification sets. Generally speaking, part of the data is used as an "exercise" of the neural network architecture, and part of the data is used as a "self-test". The basic size of each data is $1 \times 4 \times 2048$, which represents one-dimensional data. Each pump has four sensors for measurement, and 1024 points are measured as a group. Each fault type shall be trained by magnitude. The database includes the multiple source vibration signals generated by lubricating oil pump, centrifugal pump and hydraulic pump. The data set is divided into training set and verification set. It is found that the number of samples is moderate, and there is no need to expand the data volume separately. There are about 4000 samples of each type, and the total number of samples reaches 40000, which is enough. The method of directly expanding data sets is adopted to achieve the balance of data sets. The choice of optimizer is very important for the whole convolutional neural network. It determines the speed of training and the final accuracy rate, so it should be carefully selected. In this experiment, the Adam optimizer was selected, which has the following advantages. First of all, the implementation method is relatively simple, the calculation efficiency is high, and the memory requirement is small. This is very important for this experiment, because my computer can't bear the training of optimizer with high memory requirements. Hyperparameters are very interpretative, and usually require no adjustment or little fine-tuning, which also provides convenience for subsequent parameter adjustment. The updating step size is limited to a small range, that is, the initial learning rate will not change significantly. But it can automatically adjust the learning rate slightly to find lower losses faster. The reason why Adam was finally selected is that in the optimizer comparison experiment, Adam has obvious advantages over SGD, another very common optimizer.

3 Training Realization of One-Dimensional Convolutional Neural Network

The basic architecture of one-dimensional convolutional neural network has been built, and its external framework has been implemented. The specific values of internal parameters have not been updated. Then the training of the one-dimensional convolutional neural network is very necessary. After the architecture is designed, the above neural network should be trained. The essence of training is to carry out the weight self optimization process of the back propagation algorithm. The purpose of training is to change the parameters of the neural network as much as possible, so that it can more accurately deal with a class of problems, that is, fault diagnosis classification problem. The content of this chapter is to build a training framework for one-dimensional convolutional neural networks to update the network parameters and minimize the loss of its cost function.

The main content of this part is to train the one-dimensional convolutional neural network model that has been built. The purpose of training is to change the network parameters in the model to make the value of its loss function smaller, which is more accurate in theory. The main function for training needs to be written. After the compilation, the main function is used for actual training to get a training result. First of all, an experiment was carried out on the lack of BN layer. BN layer is added to obtain the fault diagnosis model of single source vibration signal for five rounds. The results show that the loss is very low, and the accuracy has reached more than 95%, which is a very good result. Then the optimization experiment is carried out, and the conclusion that Adam optimizer is better is finally obtained. Finally, the prediction ability of repeated BP units is tested. The test results show that the fault diagnosis architecture composed of full connection layer only has no scientific prediction ability, and is inferior to the hidden layer structure model.

4 Multiple Source Information Fusion Mode Selection and Architecture Optimization

There are four groups of acceleration vibration signals measured by acceleration sensors in the data set, all of which are input into the convolutional neural network. Through multi-source information fusion, the accuracy is further improved and the overall loss is reduced. After multi-source information fusion, a fault diagnosis architecture based on multi-source vibration signals and output fault types is obtained. Theoretically, the accuracy can be improved. However, in order to obtain a more stable accuracy and overall loss, architecture optimization is essential. Only by finding the most suitable structure for pump fault detection can a more reliable fault diagnosis structure be obtained. So we should do a series of experiments to find the optimal solution.

4.1 Selection and Implementation of Multi Source Information Fusion Mode

The basic concepts of multi-source information fusion is based on a variety of similar or heterogeneous information sources, by combining these information sources in time or space according to a certain standard, in order to obtain consistent interpretation of the analyzed object and make the information analysis system have better performance. The experimental data used in this experiment is measured by four different acceleration sensors for each pump, and the four groups of data can be obtained simultaneously, and each group of data can be used for fault diagnosis. According to the analysis, the data layer fusion is selected, that is, multi-source information fusion is carried out at the input. The theoretical method is to combine four groups of one-dimensional acceleration sensor measured vibration signals into a group of two-dimensional input signals at the input. The two-dimensional convolution neural network method is used to process the data and finally obtain the fault diagnosis results.

Single source vibration signals are processed before, and the size of each basic signal is 1×2048, now it forms a two-dimensional input signal, using the method similar to the matrix, before input, the data is spliced to form 4×2048. In the DATASET function, the input dimension is changed to achieve the transformation from one dimension to two dimensions, change the five layer hidden layer structure in the convolutional neural network. The multi-source information fusion in the data layer is realized to improve the accuracy of fault diagnosis and reduce the overall loss.

4.2 Optimization of Learning Rate and Hidden Layer Structure Repetition

Learning rate is the most important artificial parameter in a convolutional neural network. The optimizer has the greatest correlation with the learning rate. The training rounds selected are all 5 rounds. On average, the training time for one round is about 10 min based on the computing power of the personal computer. This experiment sets the learning rate as 3×10^{-2}, 3×10^{-3}, 3×10^{-4}, 3×10^{-5}, and then conduct five rounds of two-dimensional convolutional neural network training at a time. From the trend, only the learning rate is 3×10^{-5}. The total loss of each round is consistent with the downward trend, but the total loss of each round is high.

After optimizing the learning rate, the number of repetitions of the hidden layer structure should be optimized. The initial setting is 5 repetitions. The first convolution core is 64, which is used to identify long chain information, and the last four convolution cores are 3, which is used to identify short chain information. The long convolution kernel can get more overall information, while the short convolution kernel can get more detailed information to analyze detailed differences. In the learning rate experiment, the final result is 3×10^{-3}, 3×10^{-4}. The two learning rates have good learning characteristics, so both of them should be used in the following implementation. When the learning rate is 3×10^{-3}, the 4-layer hidden layer structure is the most appropriate. When the learning rate is 3×10^{-4}, the 3-layer hidden layer structure is the most appropriate. When the learning rate is 3×10^{-4}, the structure and learning rate of the three hidden layers are 3×10^{-3}, the experiment of 4-layer hidden layer structure is repeated to prevent unexpected data. Choose stable and stronger learning through final comparison 3×10^{-4}, the two-dimensional convolutional neural network with three hidden layers is the core of the fault diagnosis architecture.

4.3 Repeat Experiment of Good Model After Special Data Processing

After special processing of the dataset, this paper repeats the experiment again to observe the change of the accuracy and the total loss of the round. By analyzing Fig. 1 and Fig. 2, it can be found that the learning rate is 3×10^{-4}, when the 3-layer hidden layer structure repeats the experiment, the 12 round accuracy rate after data balancing is lower than that without data balancing. When the learning rate is 3×10^{-3}, when the 4-layer hidden layer structure repeats the experiment, after the data is balanced, the accuracy has been significantly improved, and is basically stable at more than 99%.The final selection of fault diagnosis architecture should be based on the data balance, because such architecture can make more balanced judgment, and will not preset which fault rarely occurs. So the learning rate is 3×10^{-3}, a two-dimensional convolutional neural network with good network parameters is trained from a 4-layer hidden layer structure to complete the final fault diagnosis architecture.

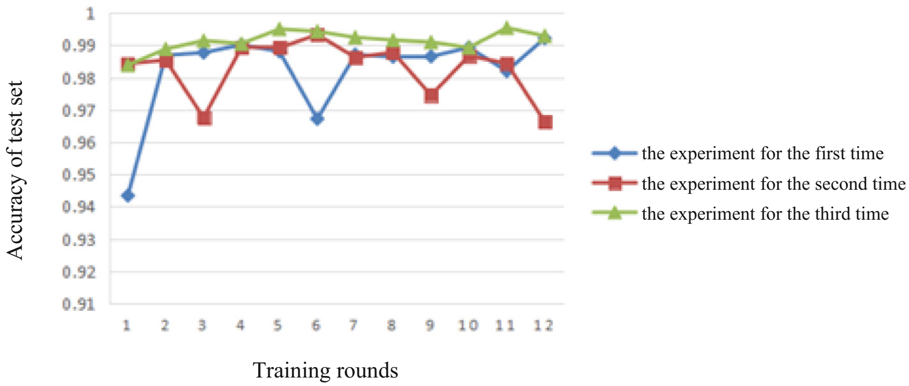

Fig. 1. The 4-layer hidden layer structure repeat experimental verification set accuracy for learning rate of 3×10^{-4}.

4.4 Final Implementation of Fault Diagnosis Network Architecture

In this experiment, Bagging's integration method is used. For trained students, the learning rate is 3×10^{-3}, the 2-dimensional convolutional neural network with 4-layer hidden

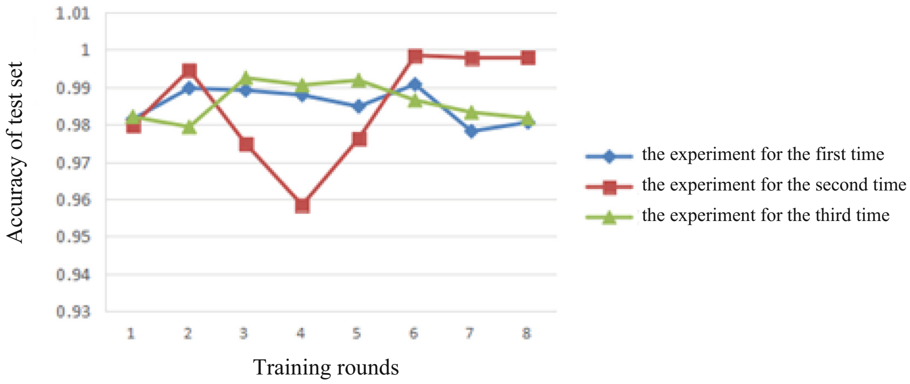

Fig. 2. The 4-layer hidden layer structure repeat experimental verification set accuracy for learning rate of 3×10^{-3}.

layer structure selects the model with high accuracy, and then Bagging is performed once. Two two-dimensional convolutional neural network models Bagging are carried out. The correctness of the verification set of these two convolutional neural networks is 99.852% and 99.805% respectively. After the two models Bagging, the accuracy of the fault diagnosis architecture has reached an amazing 99.945%, which is the first time that this experiment has raised the accuracy to three nines. As the above relatively good results are obtained, Bagging's two-dimensional convolutional neural network model is further improved to five, and the individual accuracy of the three added models is 99.113%, 99.602% and 99.566%. After five models bagging, the accuracy of the fault diagnosis architecture has reached 99.981%.

5 Conclusion

On the basis of single source vibration signal analysis, multi-source information fusion is adopted, and data sets are used as much as possible to improve the accuracy. Various experiments were carried out to optimize the structure of the convolutional neural network and get a better architecture. By adopting Bagging method in integrated learning, a fault diagnosis architecture with the final accuracy of 99.981% is obtained.

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