Multi-Attribute Convolutional Neural Network and Its Application to Bearing Fault Diagnosis

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Abstract

Existing bearing fault diagnosis methods exhibit limitations: traditional approaches involve complex mathematical computations, demonstrate suboptimal diagnostic performance, and typically can only identify fault location, making it difficult to diagnose load conditions and fault severity. Current methods utilizing convolutional neural networks employ conventional architectures wherein a single network can only output one attribute, thus cannot simultaneously diagnose multiple attributes. To enable simultaneous diagnosis of fault location, fault severity, and load conditions, this paper proposes, for the first time, a multi-attribute convolutional neural network for bearing fault diagnosis, which is trained directly using one-dimensional vibration signals. The proposed approach overcomes the shortcomings of traditional methods by enabling diagnostic results for arbitrary combinations of fault attributes, featuring fewer network parameters, a concise methodology, strong generalization capability, and high accuracy. A series of experiments conducted using bearing data from Case Western Reserve University demonstrate that the proposed method can accurately diagnose multiple attributes of bearing faults with high accuracy and excellent generalization capability.

Full Text

Preamble

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Abstract

Existing bearing fault diagnosis methods suffer from significant limitations. Conventional approaches involve complex mathematical calculations yet yield poor diagnostic performance, typically identifying only fault location while failing to diagnose load conditions and fault severity. Current convolutional neural network (CNN) methods employ traditional architectures where a single network can only output one attribute, precluding simultaneous diagnosis of multiple properties. To address the simultaneous diagnosis of fault location, fault size, and load, this paper proposes for the first time a multi-attribute convolutional neural network (MACNN) applied to bearing fault diagnosis, trained directly using one-dimensional vibration signals. The proposed method overcomes traditional shortcomings by enabling diagnosis of arbitrary combinations of fault attributes with fewer network parameters, a concise methodology, strong generalization capability, and high accuracy. Comprehensive tests using bearing data from Case Western Reserve University demonstrate that the method can accurately diagnose multiple bearing fault attributes with high precision and excellent generalization ability.

Keywords: Convolutional neural network; Fault diagnosis; Bearing; Multi-attribute

0 Introduction

Bearings are among the most widely used mechanical components in industry and also one of the most failure-prone parts. Most existing methods diagnose only bearing fault location (normal, outer ring fault, inner ring fault, and rolling element fault), while diagnosis of fault size and load conditions has significant practical value for enabling predictive maintenance rather than traditional post-failure repair, thereby reducing economic losses and component waste. Simultaneously diagnosing multiple attributes including fault location, fault size, and load presents considerable challenges, and traditional pattern recognition methods have achieved limited progress in this area. Although some scholars have considered both fault location and size, their approach treats each combination as a single class, preventing examination of individual attribute diagnostic results. Others have focused solely on fault size diagnosis for a specific fault location using complex mathematical methods. Existing bearing fault size diagnosis methods fall into two categories: regression and classification. For regression, Ju Hua proposed SVR-based quantitative bearing fault diagnosis using extracted features to train an SVR model, but this only covered outer ring faults with fault sizes uniformly distributed between 0.2–0.7 mm. Cui Lingli proposed a dynamics simulation-based method that determines fault size from the time interval between double impacts in vibration signals. For classification, most studies suffer from limited fault size data variety and treat different fault sizes as separate classes combined with fault location, resulting in numerous categories.

1 Multi-Attribute Convolutional Neural Network

1.1 Development of Convolutional Neural Networks

In 1998, Yann LeCun et al. proposed LeNet-5 using gradient descent-based back-propagation, achieving success on the MNIST handwritten digit database and drawing academic attention to CNNs, which gradually found applications in speech recognition, face recognition, and object recognition. In 2012, Hinton and his student Alex Krizhevsky proposed AlexNet, which won the ImageNet competition by a massive 11% margin over the runner-up, making CNNs a focal point in academia. Subsequently, Oxford University proposed VGGNet, Google introduced GoogLeNet, and Microsoft developed ResNet, each successively surpassing AlexNet' s records.

1.2 Advantages of Convolutional Neural Networks

As a key member of deep learning, CNNs are primarily used in two-dimensional image recognition with several advantages: (1) They automatically learn data features from large samples, eliminating the complex and cumbersome feature extraction process of traditional methods and reducing dependence on expert knowledge. (2) Their architecture employs local connectivity and weight sharing, drastically reducing network parameters, lowering training difficulty, improving training speed, and enhancing generalization capability. Consequently, scholars have begun applying CNNs to rotating machinery fault diagnosis. However, these applications only diagnose fault location without simultaneously considering fault size and load, and they use traditional CNNs that cannot diagnose multiple attributes simultaneously. In 2016, Wang Jinjiang from China University of Petroleum used CNNs for rotating machinery fault diagnosis with one-dimensional vibration data as input. In 2017, Chen Lu from Beihang University and Liu Ruonan from Xi' an Jiaotong University converted one-dimensional vibration signals into two-dimensional signals for CNN input. Also in 2017, Min Xia from the University of British Columbia proposed a multi-sensor fusion CNN approach for rotating machinery fault diagnosis.

1.3 Structure of Convolutional Neural Networks

Traditional CNNs typically consist of an input layer, convolutional layers, non-linear activation layers, pooling layers, fully connected layers, and a softmax output layer. This paper refers to such architectures as single-attribute CNNs. The core components are the convolutional, activation, and pooling layers. [Figure 1: see original paper] illustrates a typical CNN architecture.

The convolutional layer uses convolution kernels to extract features from the previous layer. Let X_i denote the feature map of layer i, with X_0 representing the input layer (typically an image). W_i is the weight matrix of convolution kernels in layer i, $\otimes$ denotes convolution operation, and b_i is the bias vector of layer i.

The nonlinear activation layer maps features from the previous layer through nonlinear functions, expressed as $F(\cdot)$ where F represents nonlinear functions such as ReLU and its variants (Leaky ReLU, Random ReLU, Parametric ReLU, Shifted ReLU, Exponential LU).

The pooling layer downsamples feature maps, reducing both dimensionality and network parameters. Max pooling is most common, expressed as $X_{s+1}(a,b) = \max_{(m,n)\in R_{s+1}} X_s(a+m, b+n)$, where R_{s+1} is the pooling window of size $s \times s$, and a, b are pixel coordinates.

CNNs aim to minimize loss comprising empirical risk (typically cross-entropy loss) and structural risk (usually L2 norm of weights).

1.4 Structure of Multi-Attribute Convolutional Neural Networks

During bearing operation, different working conditions involve varying speeds and loads, with fault attributes including fault location and size. Existing approaches for simultaneous diagnosis of these attributes fall into two categories: attribute combination and multi-network methods. The attribute combination method combines different attribute values into classes, resulting in output dimensions equal to the product of attribute value counts, leading to excessive network parameters and training difficulty while preventing individual attribute diagnosis evaluation. The multi-network method creates separate networks for each attribute, increasing diagnosis time and parameters. This paper proposes the multi-attribute convolutional neural network to overcome these limitations.

The innovation of MACNN lies in using a single network to simultaneously identify multiple fault attributes, with output dimensions equal to the sum of attribute category counts—far smaller than the product required by attribute combination methods. By sharing all layers before the output layer and only increasing output dimension, MACNN effectively reduces network parameters and testing time. In bearing fault diagnosis, MACNN can simultaneously diagnose fault location, size, load, and speed.

In MACNN architecture, the pre-softmax layers resemble single-attribute CNNs and can be designed based on classic architectures (LeNet, AlexNet, ZFNet, VGGNet, GoogLeNet, ResNet) or custom designs. The network includes input, convolutional, max-pooling, average-pooling, and softmax output layers, with activation layers following each convolutional layer. The input layer is $H \times 1 \times 1$, where H is the sample data length.

While single-attribute CNNs have a single score vector in the softmax output layer, MACNN employs M score vectors. Each bearing fault attribute is represented by one score vector whose dimension equals the number of categories for that attribute. Using Case Western Reserve University bearing data as an example, [Figure 2: see original paper] shows three attributes: fault location, fault size, and load. Thus, the softmax output layer contains three score vectors, with each vector' s maximum value position indicating the predicted category for that attribute. This enables independent diagnosis of each attribute and arbitrary combination of diagnostic results.

The risk loss for single-attribute CNNs is a single cross-entropy function, while MACNN uses a weighted average of M cross-entropy functions. For sample point i, the loss L_i in single-attribute CNNs is: $L_i = -\log\left(\frac{e^{s_{y_i}}}{\sum_{j=1}^{C} e^{s_j}}\right)$, where s is the score vector and y_i is the label.

For MACNN, the loss is: $L_i = \frac{1}{M}\sum_{k=1}^{M} L_{ik}$, where $L_{ik} = -\log\left(\frac{e^{s_{k,y_{ik}}}}{\sum_{j=1}^{n_k} e^{s_{k,j}}}\right)$. Here, M is the number of fault attributes, L_{ik} is the loss for attribute k, s_k is its score vector, n_k is its category count, and y_{ik} is the label index for attribute k.

During diagnosis, each sample point yields a multi-attribute label, and multiple sample points produce multiple labels. The final diagnosis result adopts the most frequently occurring multi-attribute label.

2 Bearing Fault Diagnosis Methodology

The CNN-based bearing fault diagnosis process comprises four steps: (1) Training database creation, (2) Multi-attribute CNN construction, (3) Network training, and (4) Bearing fault diagnosis.

Step 1: Training Database Creation
For each operating condition, sample point data are created randomly by extracting continuous data points longer than one rotation period at random positions. This random creation enhances model generalization. Sufficient sample points are generated to form the training database. Each sample point is then assigned a multi-attribute label. With M bearing fault attributes, the label is an M-dimensional vector where each dimension corresponds to the category index for that attribute.

Step 2: Multi-Attribute CNN Construction
The pre-softmax architecture can reference classic CNNs or be custom-designed. The softmax output layer consists of M score vectors, each representing one fault attribute with dimension equal to its category count.

Step 3: Network Training
The training database is used to train the MACNN, with hyperparameters tuned to achieve optimal performance and generalization.

Step 4: Fault Diagnosis
The trained MACNN processes sample points from the bearing under test, outputting M score vectors. The maximum value position in each vector determines the predicted category for that attribute, forming a multi-attribute label vector.

3 Bearing Fault Diagnosis Case Study

This case study employs the bearing fault database from Case Western Reserve University, with the experimental apparatus shown in [Figure 3: see original paper].

3.1 Database Creation

The study uses acceleration data sampled at 12 kHz from the drive end across 48 operating conditions, including: four fault locations (normal, inner ring, rolling element, outer ring), four speeds (1730, 1750, 1772, and 1797 rpm), five fault sizes (0, 7, 14, 21, and 28 mils; 1 mil = 0.001 inch), and four loads (0, 1, 2, and 3 hp). Since speed correlates with load (0 hp = 1797 rpm, 1 hp = 1772 rpm, 2 hp = 1750 rpm, 3 hp = 1730 rpm), only three attributes are diagnosed: fault location, fault size, and load. Given the limited fault size and load variations, classification rather than regression is adopted.

At the lowest speed (1730 rpm) and 12 kHz sampling, the rotation period is 416 points. As shown in [Figure 4: see original paper], sample points are created randomly by extracting 512 consecutive points (the smallest integer greater than 416) at random positions. This approach reduces network complexity and training difficulty while accelerating training and testing.

Multi-attribute labels are 3-dimensional vectors. Fault location has 4 categories (indices 1–4), fault size has 5 categories, and load has 4 categories. For example, an inner ring fault (category 2) with 0.014-inch size (category 3) under 0 hp load (category 1) receives label [2 3 1]; a normal bearing under 1 hp load receives [1 1 2].

For all 48 conditions, 600 sample points are created per condition (1800 for outer ring faults due to three installation positions), totaling 38,400 sample points with corresponding multi-attribute labels.

3.2 Multi-Attribute CNN Architecture

The network uses one-dimensional vibration signals as input. The pre-softmax architecture references VGGNet, comprising input, convolutional, max-pooling, average-pooling, and softmax output layers. Average pooling replaces fully connected layers to drastically reduce weights, lower training difficulty, and improve accuracy. Every two convolutional layers are followed by a max-pooling layer; convolutional layers preserve feature map dimensions while pooling halves them. Each convolutional layer uses Shifted ReLU activation: $\max(-1, x)$.

The 19-layer network includes 11 convolutional layers, 5 max-pooling layers, and 1 average pooling layer. The first 10 convolutional layers use 3×1 kernels; the final layer uses 1×1 kernels; all have stride 1×1. Max pooling uses 2×1 windows with stride 2×1. The input is $512 \times 1 \times 1$. [Figure 5: see original paper] illustrates the architecture.

With three fault attributes, the softmax output layer contains three score vectors: 4-dimensional for location, 5-dimensional for size, and 4-dimensional for load, totaling 13 dimensions. To preserve feature map size during 3×1 convolution, zero-padding is applied at both ends. Feature map dimensions progress as: 1, 12, 12, 12, 24, 24, 24, 48, 48, 48, 96, 96, 96, 128, 128, 128, 13, 13, 13. The final three layers' size of 13 equals the sum of score vector dimensions. The risk loss is the average of the three score vector losses:

$$L_i = \frac{1}{3}\left[-\log\left(\frac{e^{s_{1,y_{i1}}}}{\sum_{j=1}^{4} e^{s_{1,j}}}\right) - \log\left(\frac{e^{s_{2,y_{i2}}}}{\sum_{j=1}^{5} e^{s_{2,j}}}\right) - \log\left(\frac{e^{s_{3,y_{i3}}}}{\sum_{j=1}^{4} e^{s_{3,j}}}\right)\right]$$

where s_1, s_2, s_3 are score vectors for location, size, and load, and $[y_{i1}y_{i2}y_{i3}]$ is the multi-attribute label.

3.3 Hyperparameter Settings

Training hyperparameters are tuned based on performance. This study uses: Nesterov momentum SGD, early stopping, learning rate 0.003, regularization coefficient 0.0005, mini-batch size 32, momentum coefficient 0.9. Weights initialize from Gaussian distribution (mean 0, variance 0.1); biases initialize to 0.

3.4 Test 1

The database is split 6:2:2 into training, validation, and test sets per condition. Training stops at 12,000 iterations via early stopping, achieving 89.74% average test accuracy. shows the results. Since diagnosis requires correct classification of all three attributes simultaneously, most conditions exceed 99.6% accuracy, demonstrating effective multi-attribute diagnosis. The lowest accuracy (21%) occurs where load has minimal impact on vibration waveforms, making load attribute identification difficult. However, MACNN enables examination of arbitrary attribute combinations. When considering only location and size, accuracy improves to 98.96% (), confirming that load misclassification primarily reduces overall accuracy. For rolling element faults at 28 mils, three-attribute accuracy is 30.1%, but location-size accuracy reaches 100%, clearly identifying load as the error source.

Notably, the 89.74% or 98.96% accuracy represents per-sample-point accuracy. In practice, creating multiple sample points (e.g., 100) from a fault bearing and selecting the most frequent multi-attribute label yields near-zero misdiagnosis probability.

3.5 Test 2

Real bearings often operate under varying loads, requiring diagnosis of location and size with unknown load. This test simulates actual operation by withholding one load condition per fault type for testing while training on the remaining three loads. Test conditions are: normal bearing at 0 hp, inner ring fault at 1 hp, rolling element fault at 2 hp, and outer ring fault at 3 hp.

Each condition uses 600 sample points, with training conditions split 8:2 for training and validation. Training stops at 10,000 iterations. shows the 12 simulated test conditions achieve 96.3% average accuracy, demonstrating strong generalization capability.

4 Conclusion

(1) This paper proposes for the first time a multi-attribute convolutional neural network for bearing fault diagnosis with excellent performance. (2) Compared with traditional methods, MACNN directly uses raw vibration data for training and testing, offering a concise approach that automatically extracts features with superior recognition. (3) Compared with existing neural network methods, a single MACNN outputs multiple attributes, enabling individual attribute diagnosis evaluation with fewer parameters and shorter testing time. The method' s strong generalization capability is validated.

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