A Health Monitoring Method of Machine Tool Spindle Based on Multi-domain Analysis and Convolutional Neural Network

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Abstract. This paper presents a method for monitoring machine tool spindle health based on multi-domain analysis and convolutional neural network. By extracting the characteristics of data from time domain, frequency domain and time frequency domain, the data information is fully excavated automatically. Meanwhile, Convolutional neural network is used to realize fault diagnosis and classification. As a result, the fault classification results reveal high accuracy by datasheet. It proves that the method in this paper which has strong practicability and application value.

1. Introduction

The technical level and product quality of the machine tool industry are important indicators to measure the development level of a country’s equipment manufacturing industry, which are the core of basic manufacturing capabilities. The health status of the spindle of the CNC machine tool directly affects the processing quality and production efficiency. Because the spindle system is prone to failure under overload and long time, therefore, realizing the effective diagnosis of the machine tool spindle system’s faults not only has the practical significance of improving the machining accuracy and economic benefits, but also has the great strategic significance of improving the high-grade CNC machine tools and the core competitiveness of the manufacturing.

Many scholars have carried out a series of studies on fault diagnosis and made some valuable achievements in recent years, such as spindle condition monitoring based on wavelet decomposition and wavelet packet[1], based on envelope method and orthogonal empirical mode decomposition method[2] and classification and diagnosis of bearing fault types by deep learning network[3] etc. In order to solve the problems of low diagnostic accuracy and long cycle caused by the direct processing of original data due to the large amount of data[4-5]. This paper presents a fault diagnosis method of machine tool spindle system based on multi-domain analysis and convolutional neural network.

This paper is structured as follows: Firstly, the method of feature extraction based on multi domain analysis is studied, the eigenvalues of each cycle are calculated from the original data
as the sample data. Secondly, the working process of the convolutional neural network is studied, and the convolutional layer, pooling layer and full connection layer are analyzed. Finally, the data set is used for experimental verification.

2. Feature extraction based on multi-domain analysis
Due to the large amount of sensor data, direct input to the follow-up monitoring model will slow down the training speed and make it difficult to converge. Therefore, the sensor data is analyzed in multiple domains, and the feature extraction of sensor data is realized from the time domain, frequency domain, and time-frequency domain.

2.1. Analysis of time domain
The time domain describes the relationship between the signal changes over time, which generally analyzes the statistical characteristics of waveform data. Assuming the signal is \( x(i) \), the common time-domain characteristics are shown in Table 1:

| Parameter          | Equation                                      |
|--------------------|-----------------------------------------------|
| Root mean square   | \( X_{\text{RMS}} = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}} \) |
| Peak to peak value | \( X_{\text{peak}} = x_{\text{max}} - x_{\text{min}} \) |

2.2. Analysis of frequency
The time domain is an objective domain, while the frequency domain is a mathematical construction based on a pair of orthogonal bases. Through frequency domain analysis, the changes and characteristic information of the signal can be intuitively observed from the frequency dimension. Some frequency domain features are shown in Table 2:

| Parameter          | Equation                                      |
|--------------------|-----------------------------------------------|
| Barycentric frequency | \( F_{\text{BC}} = \frac{1}{n} \sum_{i=1}^{n} u(i) u(i)/2\pi \sum_{i=1}^{n} u(i)^2 \) |
| Average frequency  | \( F_{\text{MF}} = \frac{1}{n} \sum_{i=1}^{n} u(i) \) |

2.3. Analysis of time frequency
However, both time-domain analysis and frequency-domain analysis are aimed at the analysis and processing of a single dimension, and it is impossible to observe the changes and characteristics of signals from the two dimensions of time and frequency. Therefore, this paper proposes a wavelet packet decomposition algorithm for further feature extraction. In this paper, wavelet energy entropy, scale entropy and singular entropy are used as the characteristic parameters in the time-frequency domain.

3. CNNs
In recent years, due to the convolution network whose input data is lattice and the convolution algorithm is adopted, it is favored by many scholars, especially for multi-sensor data processing\[^5\]. The convolutional neural network mainly includes convolutional layer, pooling layer, fully connected layer and output layer what will be briefly introduced below.
3.1. Convolutional layer
The implementation process of the convolutional layer mainly includes two parts. Firstly, the convolution filter is used to convolute each region of the image in turn, and the example is shown in Fig 1. Secondly, the result of convolution is input into the activation function to get the final result of convolution layer.

![Figure 1. Schematic diagram of convolution process.](image)

3.2. Pooling layer
Generally, the operation of pooling layer is performed after convolution layer. In pooling operation, firstly, a reasonable pooling method is selected. Secondly, the convoluted image is divided into multiple regions. Finally, the final result is obtained by region operation. Fig. 2 is the schematic diagram of pooling of maximum and average values.

![Figure 2. Schematic diagram of pooling process.](image)

3.3. Full connection layer and classification layer
Through the convolutional layer and the pooling layer, the original data can be mapped to the feature space of the hidden layer. On the contrast, the fully connected layer maps the learned ‘distributed feature representation’ to the sample label space. The following is a simple analysis of the full connection layer.

![Figure 3. Schematic diagram of full connection layer process.](image)

As can be seen from the figure above, the output of the fully connected layer can be expressed by equation (1). After the output of the full connection layer is obtained, the Softmax classifier is used in this paper.

$$
\begin{bmatrix}
  a_1 \\
  \vdots \\
  a_m
\end{bmatrix}
= 
\begin{bmatrix}
  w_{11} & w_{12} & \ldots & w_{1(n-1)} & w_{1n} \\
  \vdots & \vdots & \ddots & \vdots & \vdots \\
  w_{m1} & w_{m2} & \ldots & w_{m(n-1)} & w_{mn}
\end{bmatrix}
\begin{bmatrix}
  X_1 \\
  \vdots \\
  X_n
\end{bmatrix}
+ 
\begin{bmatrix}
  b_1 \\
  \vdots \\
  b_m
\end{bmatrix}
$$

(1)
4. Experiment

This paper takes the Case Western Reserve University Bearing Data. According to the original data, the faults are divided into four categories, namely, inner race fault, outer race fault, ball fault and normal. Table 3 shows the characteristic values of each state in a period which were calculated the characteristic value in each state separately.

| Bearing state       | peak to peak | average | variance | crest factor | kurtosis |
|---------------------|--------------|---------|----------|--------------|----------|
| Inner race fault    | 5.5806       | 0.0108  | 0.7287   | 3.6167       | 3.4430   |
| Outer race fault    | 6.6556       | 0.0032  | 0.1742   | 8.1359       | 26.3170  |
| Ball fault          | 1.0435       | 0.0326  | 0.0230   | 3.3959       | 3.3875   |
| Normal              | 0.4284       | 0.0112  | 0.0040   | 3.1148       | 3.1848   |

And then, the convolutional network designed in this paper includes two layers of convolutional layers, two-layer pooling layers and fully connected layers, etc. The related hyperparameters are set as shown in Table 4:

|       | filter | strides | depth | strides | padding | pool method |
|-------|--------|---------|-------|---------|---------|-------------|
| convexional layer | 5×5    | 16      | 1     | 1       | SAME    | Max         |
| pooling layer     | 2×2    |         | 2     | SAME    |         |             |
| convexional layer | 5×5    | 32      | 16    | 1       | SAME    | Max         |
| pooling layer     | 2×2    |         | 2     | SAME    |         |             |

The number of samples in the training set is 1092 and the number of samples in the test set is 293. At the same time set the learning rate to 0.002 and the number of iterations to 200.

![Figure 4](image)

**Figure 4.** Schematic diagram of accuracy and loss function.

As can be seen from the above figure, after 20 iterations, the cost function of the training set converges. The accuracy of the test set was 99.28% by using the trained network. It is verified that this method can achieve better classification effect.

5. Conclusion

This paper presents a fault diagnosis method based on deep convolutional neural network. For traditional diagnosis methods, this article first extracts raw data from a multi-domain perspective, and uses feature values as inputs to convolutional neural networks for fault diagnosis. Compared with traditional methods, it reduces the amount of calculation and saves training time. The experimental verification shows that this method can obtain better results.
6. References
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