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INTEGRATING EMPIRICAL MODE DECOMPOSITION AND CONVOLUTIONAL NEURAL NETWORK FOR EFFICIENT FAULT DIAGNOSIS IN METALLURGICAL MACHINERY

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The paper introduces an innovative framework for rotating machinery fault recognition by combining Empirical Mode Decomposition (EMD) and Convolutional Neural Network (CNN). This novel approach integrates feature extraction and selection, utilizing deep learning for precise classification of transmission components faults. Our method achieves an impressive accuracy of 98,97 %. This robust technology significantly enhances the detection and diagnosis of transmission faults in metallurgical plant, providing an efficient solution for intelligent manufacturing applications.

Keywords: metallurgical machinery, transmission, diagnosis of faults, intrinsic mode functions, convolutional neural networks

INTRODUCTION

The restoration of the mechanical and electrical systems in a metallurgical plant relies heavily on timely and accurate fault detection. Recent advancements in intelligent metallurgical manufacturing have led to the development of data-driven diagnostic methods. Currently, driven by artificial intelligence (AI) innovations, significant technological progress has been achieved in metallurgical production. AI methods encompass machine learning (ML) and deep learning (DL) neural network algorithms[1]. Deep learning networks typically depend on extensive datasets and have proven effective in the fault diagnosis of various rotating equipment in the metallurgical field, surpassing other machine health monitoring systems in classification accuracy[2, 3]. Mechanical fault detection has become a primary concern in many industries, as these faults can disrupt operations and increase operational costs. Furthermore, a failure in one component of a transmission part may trigger a cascade of failures in other components[4]. Vibration signal analysis plays a crucial role in distinguishing between normal and abnormal mechanical operation. This analysis, conducted in both the time and frequency domains, aids in identifying faults in multiple transmission components of metallurgical plant machinery.

This article decomposes complex data signals into simpler constituent parts, facilitating the easier identification and analysis of potential issues. This method is particularly well-suited for handling nonlinear and non-stationary time series data, providing a robust solution for diagnosing faults in transmission components.

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METHOD

The data processed through EMD and subsequently subjected to feature extraction via CNN constitutes a powerful combination, particularly suitable for the analysis and pattern recognition of complex data. The detailed steps are as follows:

In the first step, I will employ EMD to decompose the time series data $s(t)$ of the metallurgical lathe's transmission components into a series of intrinsic mode functions (IMFs). Using interpolation, upper and lower envelope lines are constructed. The average of these upper and lower envelope lines is calculated, and this average is subtracted from the original data. The resulting outcome serves as a new dataset, and the above steps are iteratively repeated until the conditions for IMF are met. The decomposed IMF is subtracted from the original data, and the entire process is repeated for the remaining data until all data is decomposed into IMFs.

$$s(t) = \sum_{i=1}^{n} \mathrm{IMF}_{\mathrm{i}}(t) + r(t) \tag{1}$$

where $\mathrm{IMF}_{\mathrm{i}}(t)$ is the i-th Intrinsic Mode Function, and $r(t)$ is the residual function representing the trend component in the data. For $\mathrm{IMF}_{\mathrm{i}}(t)$, the difference in the number of local maxima and minima is at most one over the entire length of the dataset, and at any given moment, the average of the upper envelope formed by all local maxima and the lower envelope formed by all local minima is zero. The EMD decomposition is illustrated in Figure 1.

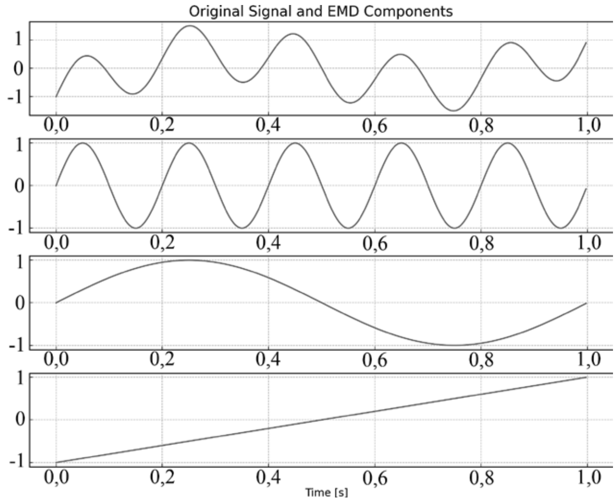

Figure 1 The EMD decomposition diagram

The original signal is composed of two oscillatory modes (IMF1 and IMF2) and a linear trend. The plot shows these components separately, following the principle of EMD where a complex signal is broken down into its intrinsic oscillatory modes and a residual trend.

The second step involves applying layer normalization to each IMF to ensure they have appropriate mean and variance. This contributes to improving training stability and convergence speed. Representing an IMF as $x = [x_1, x_2, \ldots, x_n]$, where n is the length of the IMF, the corresponding mean and variance are computed as per formulas (2) and (3).

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2 \tag{3}$$

Standardizing the IMF using mean and variance,

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}} \tag{4}$$

where ε is a small constant employed to prevent division by zero errors. The standardized IMF undergoes scaling and shifting to obtain the final output of layer normalization.

$$y_i = \gamma \hat{x}_i + \beta \tag{5}$$

where γ and β are learnable parameters that enable the network to learn appropriate scaling and shifting.

The third step involves constructing a CNN network, where each convolutional layer comprises a set of learnable filters that slide over the input data (convolution operation) to generate feature maps. This process contributes to the building and feature extraction. For a given input X and filter K, the convolution operation can be expressed as

$$F(i,j) = (K * X)(i,j) \tag{6}$$

where * denotes the convolution operation, and $F(i,j)$ is an element on the feature map. Following each convolutional layer, a non-linear activation function Rectified Linear Unit (ReLU) as shown in Figure 2 is applied to enhance the network's non-linear characteristics, enabling it to learn more complex features.

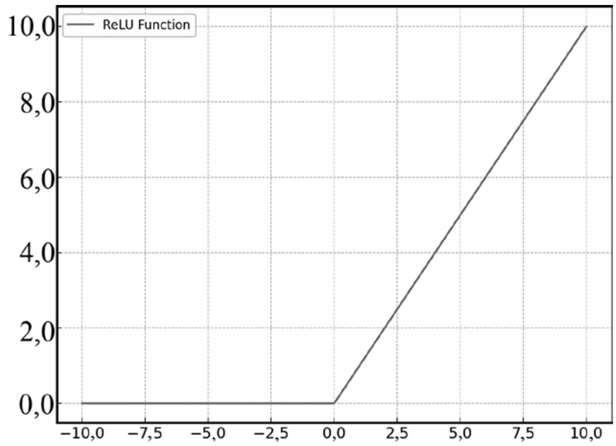

Figure 2 The ReLU curve diagram

The ReLU function is defined as shown in formula (7).

$$\mathrm{ReLU}(x) = max(0, x) \tag{7}$$

Achieving average pooling is implemented by computing the mean over each pooling window. Assuming we have a pooling window of size $k \times k$, for each position (i, j) in the feature map, the output O_{ij} of average pooling is calculated as follows:

$$O_{ij} = \frac{1}{k^2}\sum_{p=1}^{k}\sum_{q=1}^{k} I_{i+p-1,j+q-1} \tag{8}$$

where I is the input feature map, $(i + p - 1, j + q - 1)$ represents the position in the pooling window.

After the fully connected layers, it is common to use the softmax function to transform the network's output into a probability distribution for classification. Assuming we have an output vector $z = [z_1, z_2, \ldots, z_C]$ with C categories, where z_i represents the network's score or activation value for the i-th category. The calculation formula for the softmax function is as follows:

$$\mathrm{softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{9}$$

where $\mathrm{softmax}(z)_i$ is the probability of the i-th category calculated through the softmax function. This function transforms each score into a probability value, ensuring that the sum of probabilities for all categories is equal to 1.

In practical applications, the softmax function is commonly used in conjunction with the cross-entropy loss function to minimize the gap between the model's output and the actual labels during training. Let $y = [y_1, y_2, \ldots, y_C]$ represent the one-hot encoded actual category labels, where only one element is 1, and the rest are 0. The cross-entropy loss function is as follows:

$$\mathrm{CrossEntropy}(y, \mathrm{softmax}(z)) = -\sum_{i=1}^{C} y_i \cdot \log(\mathrm{softmax}(z)_i) \tag{10}$$

In our study, we employ accuracy (Acc) as the metric to evaluate the performance of fault diagnosis models. The formula for calculating Acc is as follows:

$$Acc = \frac{TP + TN}{TP + FP + FN + TN} \tag{11}$$

where TP represents the instances where the model correctly predicts the presence of faults in the transmission components. TN indicates the instances where the model accurately predicts the absence of faults in the transmission components. FP signifies the instances where the model incorrectly predicts normal samples as having faults in the transmission components. FN denotes the instances where the model erroneously predicts samples with faults in the transmission components as normal.

TRANSMISSION COMPONENTS OF METALLURGICAL PLANT MACHINERY

Figure 3 The exemplar of transmission components

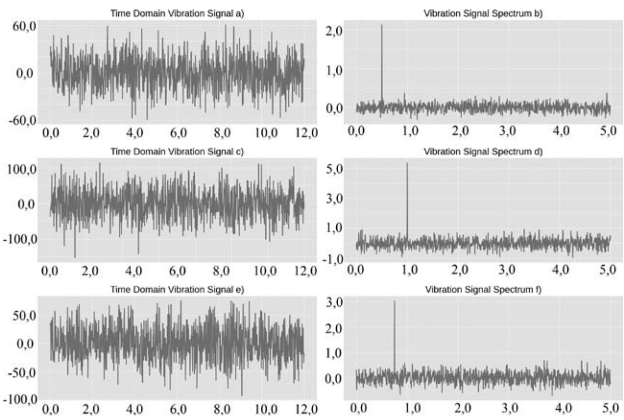

Figure 4 The signal of transmission components

where a), c), e) represents the time domain vibration signal and b), d) and f) denotes the corresponding frequency spectrum

The experiments in this paper involve spiral transmission devices of two types of dynamic axle-wheel systems. The wear and tear of the devices under different usage durations is analyzed using time-domain vibration signals and frequency spectrum signals. The exemplar of transmission components is depicted in Figure 3, with its corresponding signals illustrated in Figure 4.

After five rounds of cross-validation, we successfully trained a model for detecting faults in transmission components. The model demonstrated encouraging performance on various subsets of data, achieving an average accuracy of 98,97 %. This significant improvement in accuracy indicates the efficient capability of our model to detect potential faults in the devices.

CONCLUSION

It propose a fault diagnosis approach for spiral transmission devices in dynamic axle-wheel systems by EMD and a CNN network model. This method decomposes complex data signals into simpler components, employing deep learning techniques to identify and analyze potential fault issues. It provides a robust tool for fault diagnosis.

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Note: The responsible for English language is X.F. Tang, Liaoning, China