EMD-CNN model based condition monitoring and fault warning for power overhead optical cable communication

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Abstract. Optical fiber communication has become the main communication mode of power communication in China. As the carrier and foundation, the stability and security of power communication optical cable is directly related to the reliability and security of power communication network in China. In this paper, the idea of in-depth learning is introduced into the condition monitoring of communication optical cable, taking the all-dielectric self-supporting optical cable (ADSS) as an example. By transforming the image into picture set and choosing the appropriate depth neural network model to analyse the picture, the condition monitoring of communication optical cable can be realized.

1. Introduction
With the development of power industry and the maturity of control technology, power cable Patrol has gradually changed from manual patrol to remote monitoring. However, remote monitoring needs human eyes to judge the failure of optical cable[1]-[2]. However, due to complex environmental factors, human eye judgment is prone to misjudgement, resulting in irreversible consequences. [3]-[5]Therefore, the use of effective intelligent algorithms instead of human eyes for automatic identification of target optical fibers has become a research hotspot.

In 2019, the State Grid proposed to build a ubiquitous Internet of Things, which provides a technical basis for full-line optical fiber video surveillance. With the continuous growth of the national economy, the scale of the power grid continues to expand, the number of communication optical cables built under complex terrain conditions is increasing, and the number of communication optical cables is multifaceted, wide-distance and long-distance.[6] The construction of a set of advanced optical fiber fault intelligent identification algorithm will provide an effective means for the safe operation of optical cable.[7]

With the rapid development of computer technology, multimedia technology and artificial intelligence technology, image processing technology is more and more widely used, and has made some achievements in scientific research, education and management, medical and health, military and other fields. Image processing refers to the use of computers to process images, emphasizing the exchange between images[8]. The main goal is to process images to improve the visual effect of images and to provide a basis for image recognition in the later stage. Image recognition is a technology that processes, analyses and understands images by computer to recognize targets and objects of different modes.

EMD-CNN model-based condition monitoring and fault warning of power overhead optical cable communication is to convert the existing video into frame pictures to build image data sets, train the
image data to obtain convolutional neural network model, and then use the network model to classify and recognize the image, output the type of pictures tested and the accuracy of recognition.

In this paper, the idea of in-depth learning is introduced into the condition monitoring of communication optical cable, taking the all-dielectric self-supporting optical cable (ADSS) as an example. By choosing the appropriate depth neural network model, data analysis of the collected optical cable parameters is carried out, thus realizing the function of monitoring the status of communication optical cable.

2. EMD-CNN Feature Extraction and Fault Recognition

Generally, communication data signals have non-stationary and non-linear characteristics, and a large number of labeled fault data can not be obtained in practical application. In view of this situation, an intelligent diagnosis method of bearing fault based on empirical mode decomposition feature extraction and deep learning state recognition is proposed[9]. Firstly, EMD algorithm is used to decompose the non-stationary bearing data into several stationary mode functions; then the EMD energy entropy of vibration signals and the time-domain and frequency-domain statistical features of each IMF component are extracted to form feature vectors; then the selected sensitive features are input into the in-depth learning network for fine-tuning training, and the feature learning and state recognition classification model of rolling bearings is obtained. The experimental results show that this method can effectively extract fault features and improve the accuracy of diagnosis.[10]

2.1. Feature Extraction and Fault Diagnosis Based on EMD and Energy Entropy

**EMD method.** The essence of EMD method is to decompose a non-stationary signal into a finite number of eigen-mode functions. This decomposition is based on the local characteristics of the time scale of the original signal. Therefore, each IMF component contains the local characteristics of the original signal at different time scales. To be an IMF component, the following two conditions must be met simultaneously:

1. The number of zero-crossing points and the number of extreme points differ to one in many phases;
2. The mean value of the upper envelope formed by connecting the local maximum point and the lower envelope formed by connecting the local minimum point is zero, that is, they are symmetrical relative to the time axis.

The steps of EMD decomposition for signal \( x(t) \) are as follows.

1. The input signal \( x(t) \) is calculated to obtain its local maximum and local minimum. All local maximum points are connected to form upper envelope \( E_u(t) \) and all local minimum points are connected to form lower envelope \( E_l(t) \).
2. To calculate the average \( m_i(t) = \frac{E_u(t) + E_l(t)}{2} \) of the upper and lower envelopes, there is \( h_i(t) = x(t) - m_i(t) \).

Ideally, if \( h_i(t) \) satisfies the IMF condition, then \( h_i(t) \) is the first IMF component.

3. If \( x(t) \) does not satisfy the conditions of IMF, then \( h_i(t) \) is used as input signal and (1) (2) steps are repeated. If the mean value of the upper and lower envelopes of \( h_i(t) \) is \( m_{i+1}(t) \), we can further judge whether \( h_{i+1}(t) = h_i(t) - m_{i+1}(t) \) can satisfy the constraints of IMF. If not, the above steps will be repeated \( K \) times until \( h_{i+k}(t) = h_{i+k-1}(t) - m_{i+k}(t) \) (\( k = 1, 2, \ldots, N \)) satisfies IMF constraints. Thus, the first IMF component \( c_1(t) \), which represents the highest frequency component in \( X(t) \), is obtained.
(4) $c_1(t)$ is separated from the original signal $x(t)$ and a new signal with high frequency components removed is obtained.

$$r_1(t) = x(t) - c_1(t)$$

Repeat step $r_1(t)$ as the original input signal (1) (2) (3) to get the second IMF component $c_2(t)$. Repeat n times to get n IMF components, that is, get the following formula:

$$\begin{cases}
    r_1(t) - c_1(t) = r_2(t) \\
    \vdots \\
    r_{n-1}(t) - c_{n-1}(t) = r_n(t)
\end{cases} \quad (1)$$

When $r_n(t)$ becomes a monotone function, the loop ends. It can be obtained from the above formulas.

$$x(t) = \sum_{i=1}^{n} c_i - r_n \quad (2)$$

In the formula, the residual function $r_n(t)$ represents the average trend of the signal. Each IMF component $c_1(t), c_2(t), \ldots, c_n(t)$ contains components of different time scales of signals, and its time scales are from small to large in turn. Therefore, each component correspondingly contains different frequency bands from high to low, each frequency band contains different frequency components, and it will change with the change of the signal itself.

EMD Energy Entropy The vibration signal is decomposed by EMD to obtain n IMF components $c_1, c_2, \ldots, c_n$. If the residual components are neglected, the total energy of the original signal can be obtained by adding the energy of each IMF. Because each IMF component contains different frequency components, each IMF component has different energy distribution in frequency domain. Assuming that the energy of each IMF is $E_1, E_2, \ldots, E_n$ and the total energy of the original signal is $E$, the energy entropy of EMD can be defined as:

$$H_{EN} = -\sum_{i=1}^{n} \frac{E_i}{E} \log \frac{E_i}{E} \quad (3)$$

In the formula, $p_i = E_i / E$ denotes the proportion of energy of eigenmode function $IMF_i$ in total energy ($E = \sum_{i=1}^{n} E_i$). When different fault types occur, the corresponding EMD energy entropy values are different. Therefore, EMD energy entropy can characterize fault characteristics and then distinguish fault types.

2.2. The Layering of Convolutional Neural Networks

The essence of CNN is to construct several filters that can extract data features, and extract hidden topological features between data by convoluting and pooling input data layer by layer. With the increase of the number of layers, the extracted features are more and more abstract. Finally, these abstract features are merged through the full connection layer, and the classification and regression problems are solved through the software Max or sigmoid activation function.[11]-[12] One of the characteristics of CNN is that it can extract the local features of input data and abstractly generate high-level features layer by layer to effectively realize fault diagnosis and recognition.

Because convolution neural network is a multi-level neural network, it includes filtering level and classification level. The filter level is used to extract the features of the input signal, and the classification level is used to classify the features learned. The parameters of the two-level network are trained together. The filter level consists of three basic units: convolution layer, pooling layer and activation layer. The classification level is generally composed of full connection layer.

(1) Convolutional layer
Convolution kernels are used to convolute local regions of input signals (or features) and generate corresponding features. The most important feature is weight sharing, that is, the same convolution core will traverse the input at a fixed step size. Weight sharing reduces the network parameters of convolution layer, avoids over-fitting caused by too many parameters, and reduces the memory required by the system. In practice, correlation operations are mostly used to replace convolution operations, which can avoid flipping the convolution core when backpropagation occurs. Specific convolution layer operations are shown as follows:

\[
y^{(i,j)} = K_i * x^{(i,j)} = \sum_{j=0}^{w-1} K_i^{(j)} x^{(i,j+j)}
\]  

K is the j-th weight of the first convolution core in layer L, X is the j-th convolution local region in layer L, and W is the width of the convolution core.

In the operation of one-dimensional convolution layer, each convolution core traverses the convolution layer once and performs convolution operation at the same time. Take the first convolution nucleus as an example. In the convolution operation, the coefficients corresponding to the neurons in the convoluted area are multiplied, and then the convolution nucleus is moved with the step size of 1. The previous operation is repeated until the convolution nucleus traverses all the regions of the input signal.

(2) Activation layer

After convolution operation, the activation function transforms the Logits value of each convolution output nonlinearly. The purpose of the activation function is to map the original linear non-separable multidimensional features to another space. Since the derivative of ReLU function is always 1 when the input value is greater than 0, the gradient dispersion phenomenon is well overcome, so this paper uses ReLU as the activation function of convolutional neural network. The ReLU function is shown in the following formula:

\[
d^{(i,j)} = f(y^{(i,j)}) = \max\{0, y^{(i,j)}\}
\]

\(d^{(i,j)}\) is the activation value of convolution layer output y.

(3) Pooling layer

The width and depth of the original feature are sampled to the output by adjusting the size and step size of the pooling operation. The downsampling operation adopted in this paper is maximum pooling. It takes the maximum value in the perceptual domain as the output, which has the advantage of obtaining position-independent features.

\[
p^{(i,j)} = \max_{(j-1)W + 1 \leq j \leq W} \{d^{(i,j)}\}
\]

In the formula, a is the activation value of the t-th neuron in the first frame of the L-level, W is the width of the pooled area and P is the width of the pooled area.

(4) Fully connected layer

Full connection layer classifies the features extracted from filter level. Specifically, the output of the last pooling layer is first spread out into one-dimensional feature vectors as the input of the full connection layer, and then the input and output are fully connected. The activation function used by the implicit layer is ReLU, and the activation function used by the output layer is Softmax function.

\[
z^{(i,k)} = \sum_{j=1}^{W} W^{(i,j)} d^{(j)} + b
\]

In the formula, W is the weight value between the first neuron in L layer and the jth neuron in L + 1 layer, Z is the Logits value of the jth output neuron in L + 1 layer, and b is the bias value of all neurons in L layer to the jth neuron in L + 1 layer.

(5) objective function

The output of an input signal in the neural network should be consistent with its target value. The function to evaluate this consistency is called the objective function of the neural network. Commonly used objective functions are square error function (and cross-entropy loss function). The soft max
value of the actual output of convolutional neural network is $q$, and its target distribution $P$ is a vector of one-hot type. That is, when the target category is $j$, $P^j = 1$, otherwise $P^j = 0$.

$$L = \frac{1}{m} \sum_{i=1}^{m} (p^j_i - q^j_i)^2$$  \hspace{1cm} (8)

$$L = -\frac{1}{m} \sum_{i=1}^{m} \sum_{j} p^j_i \log q^j_i$$  \hspace{1cm} (9)

2.3. Convolutional Error Back Propagation Neural Network

Error back propagation is a key step in weight optimization of neural networks. The main method is to first solve the derivative of the objective function with respect to the last neuron layer, and then calculate the derivative of the objective function with respect to the ownership value layer by layer from back to front through the chain rule.

1) Reverse Derivative of Full Connection Layer

First, the derivative of the objective function $L$ with respect to the last level Logits value $z^{l+1(j)}$ is calculated.

$$\frac{\partial L}{\partial z^{l+1(j)}} = \sum_{i} p_i^j q_i^j - p_i^j$$  \hspace{1cm} (10)

Calculating the Derivative of the Weight $W^l_{ij}$ and Bias $b^l_j$ of the Full Connection Layer Object Function $L$ with respect to Full Connection Layer

$$\frac{\partial L}{\partial W^l_{ij}} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot \frac{\partial z^{l+1(j)}}{\partial W^l_{ij}} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot a^{(i)}$$  \hspace{1cm} (11)

$$\frac{\partial L}{\partial b^l_j} = \frac{\partial L}{\partial z^{l+1(j)}} \cdot \frac{\partial z^{l+1(j)}}{\partial b^l_j} = \frac{\partial L}{\partial z^{l+1(j)}}$$  \hspace{1cm} (12)

Finally, the derivatives of the activation value $a^{(i)}$ and Logits value $z^{(j)}$ of the fully connected hidden layer with the activation function $L$ as ReLU are calculated

$$\frac{\partial L}{\partial a^{(i)}} = \sum_{j} \frac{\partial L}{\partial z^{l+1(j)}} \cdot \frac{\partial z^{l+1(j)}}{\partial a^{(i)}} = \sum_{j} \frac{\partial L}{\partial z^{l+1(j)}} \cdot W^l_{ij}$$  \hspace{1cm} (13)

$$\frac{\partial L}{\partial z^{l(i)}} = \frac{\partial L}{\partial a^{(i)}} \cdot \frac{\partial a^{(i)}}{\partial z^{l(i)}}$$  \hspace{1cm} (14)

2) Reverse derivation of pool layer

After calculating the $\frac{\partial L}{\partial a^{(i)}}$ value from the above formulas, the derivative of the objective function $L$ with respect to the weight $W^{l+1}_{ij}$ of the fully connected hidden layer and the offset term $b^{l+1}_j$ is continued to be solved. After solving the derivatives of the Logits and weights of the objective function $L$ with respect to the fully connected layer, the derivatives of $L$ with respect to the parameters of the pooling layer are calculated. Since the pooling layer has no weights, only the derivatives of $L$ for the input neurons of the pooling layer need to be calculated.

For maximum pooling, the specific method is to record the maximum position of pooling area in forward propagation, $\max_{(j=1) \wedge W^{l+1} \wedge j \preceq j_{max}} \{a^{l+1(j)}\} = a^{l+1(j_{max})}$. In reverse propagation, the derivative is transmitted to the $t_m$ neuron, and other neurons are not involved in transmission, that is, the derivative is zero.

$$\frac{\partial L}{\partial a^{l+1(j)}} = \frac{\partial L}{\partial p^{l+1(j,j)}} \cdot \frac{\partial p^{l+1(j,j)}}{\partial a^{l+1(j)}} = \frac{\partial L}{\partial p^{l+1(j,j)}} (t = t_m)$$  \hspace{1cm} (15)
3) Reverse derivation of convolution layer
First, the derivative of the Logits value of L for each convolution layer is calculated, because the convolution layer uses the ReLU activation function.

\[
\frac{\partial L}{\partial y^{(i,j)}} = \frac{\partial L}{\partial a^{(i,j)}} \frac{\partial a^{(i,j)}}{\partial y^{(i,j)}} = \frac{\partial L}{\partial a^{(i,j)}} (y^{(i,j)} > 0)
\]  \hspace{1cm} (16)

Next, the derivative of L with respect to the input value \(x^{(i,j)}\) of the convolution layer is calculated.

\[
\frac{\partial L}{\partial x^{(i,j)}} = \sum_i \frac{\partial L}{\partial y^{(i,j)}} \frac{\partial y^{(i,j)}}{\partial x^{(i,j)}} = \sum_i \frac{\partial L}{\partial y^{(i,j)}} \sum_{j'=0}^{w-1} K_i'(j')
\]  \hspace{1cm} (17)

Finally, the derivative of L with respect to convolution kernel \(K_i'(j')\) is calculated.

\[
\frac{\partial L}{\partial K_i'(j')} = \frac{\partial L}{\partial y^{(i,j)}} \frac{\partial y^{(i,j)}}{\partial K_i'(j')} = \frac{\partial L}{\partial y^{(i,j)}} \sum_j x^{(j)}
\]  \hspace{1cm} (18)

3. Case analysis
The optical cable images collected are classified into four categories: connection point (Case 1), upward extension cable (Case 2), downward extension cable (Case 3) and cross line (Case 4). Table 1 shows the number of different types of image data sets.

Table 1. Different types of image datasets
| data set | Total | Number of training | Number of tests |
|----------|-------|--------------------|-----------------|
| Data1    | 1748  | 1637               | 111             |
| Data2    | 2944  | 2784               | 160             |
| Data3    | 1674  | 1462               | 212             |

In the example, the data of all scenarios are trained and iterated 100,000 times. The attenuated learning rate is adopted. The learning rate of the first 50,000 generations is 0.001, and that of the last 50,000 generations is 0.0001. In order to demonstrate the effectiveness of the proposed method, the comparison method is the original CNN method. The experimental environment of this paper is Ubuntu 16.04 system, Inter Core i7-8700k and Nvidia GTX1080Ti graphics card. The algorithm is trained and tested with TensorFlow framework.

Table 2. Test Accuracy of EMD-CNN in Four Data Sets
| data set | Case1 | Case2 | Case3 | Case4 |
|----------|-------|-------|-------|-------|
| Data1    | 0.948 | 0.931 | 0.906 | 0.917 |
| Data2    | 0.925 | 0.912 | 0.962 | 0.904 |
| Data3    | 0.964 | 0.897 | 0.902 | 0.917 |

Table 3. Test Accuracy of CNN in Four Data Sets
| data set | Case1 | Case2 | Case3 | Case4 |
|----------|-------|-------|-------|-------|
| Data1    | 0.871 | 0.908 | 0.833 | 0.861 |
| Data2    | 0.898 | 0.873 | 0.921 | 0.875 |
| Data3    | 0.915 | 0.886 | 0.894 | 0.85  |

From the test set, it can be seen that the test results of the original CNN in different data sets can reach more than 80%. The test accuracy of the improved EMD-CNN algorithm proposed in this paper basically reaches more than 85%. Compared with the original CNN model, it has obvious improvement, and has good adaptability in different scenarios, and can better detect the faults of optical cables.
4. Conclusion
In order to detect the faults of power communication optical cables in time by monitoring video, this paper combines the most effective in-depth learning method to realize the automatic identification of the faults of optical cables. In this paper, based on EMD-CNN model, a fault identification method for Reasoning-Oriented communication optical cable is proposed. The image data set is constructed from image conversion frame images, and the data set is divided into different scenarios. By choosing appropriate depth neural network model, the data set is analyzed, so as to realize the condition monitoring of communication optical cable.

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