Research article

A quantitative identification method based on CWT and CNN for external and inner broken wires of steel wire ropes

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ABSTRACT

The detection of broken wires in steel wire ropes is of great significance for the production safety. However, the existing identification techniques mainly focus on the external broken wires problem. Here, the artificial feature extraction is one of the most important methods, while only the prior knowledge of the artificial feature extraction method is adequate, the identification precision can be satisfied. Therefore, it is still a challenge to realize intelligent diagnosis for the broken wires. Besides, the identification of internal broken wires problem is still not well solved. In this paper, a quantitative identification method based on continuous wavelet transform (CWT) and convolutional neural network (CNN) is proposed to solve the internal and external broken wires identification problem. The key technology of this research is that the fault information from the time-frequency images converted by the magnetic flux leakage (MFL) signals can be automatically extracted through a designed CNN. The main innovation is that the complex signal processing work can be eliminated and the internal and external broken wires can be accurately identified simultaneously by combining CWT and CNN. The experimental results of a steel wire rope test rig are compared with the traditional recognition method, which shows that the proposed method achieved significant improvement on detection accuracy and recognition performance.

1. Introduction

Steel wire ropes have important applications in mining, elevator and other scenes. Considering the loading condition and the harsh working environment, it is necessary to monitor and inspect the steel wire rope regularly [1, 2, 3]. As a common damage of the steel wire rope, the broken wire will reduce the residual strength of the rope and affect the production safety [4, 5]. Moreover, the number of broken wires within a certain length is usually taken as an important criterion by many organizations to evaluate whether the wire rope needs to be replaced. Therefore, it is important to identify the number and type of broken wires for health monitoring purposes.

Recently, the problem of the quantitative identification of broken wires in wire ropes has been widely investigated over the world [6, 7, 8, 9, 10, 11, 12]. Cao et al. [6] proposed an identification method to classify several typical broken wires by the back propagation (BP) network, in which the Karhunen-Loeve (KL) transform method was deployed to extract the fault features of the two-dimensional magnetic flux leakage (MFL) signal. Zhang et al. [7] applied compressed sensing wavelet filtering to obtain the image expression of the MFL signal with improved signal-to-noise ratio, where the broken wire characteristics extracted from the MFL images are taken as the inputs of a BP network for fault classification. Subsequently, a denoising method based on ensemble empirical mode decomposition (EEMD) was designed to remove system noise [11]. Kim and Park [8] explored a non-destructive evaluation method for steel wire ropes based on the artificial neural network (ANN), in which the damage indexes established by the generalized extreme value (GEV) distribution and the general damage features are combined for the quantitative identification of the different damage. Huang et al. [9] proposed a method to identify surface broken wires using computer vision techniques and a convolutional neural network (CNN), which can automatically extract the fault features of the surface images of the wire rope to overcome the limitation of manual feature extraction. Liu et al. [12] proposed a wire rope defect recognition method based on signal analysis and CNN, and evaluated its performance through accuracy, error, run time, etc. Zhang et al. [10] designed induction coil and Hall sensor to collect damage signals, and established two-layer neural network to quantitatively identify surface broken wire and inner broken wire of rope strand.

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However, current methods mainly focus on the identification of external broken wires, and there is a lack of research on the classification of internal broken wires. The MFL signals of internal broken wires are very weak, and the internal and external broken wires with different sizes may cause similar oscillation changes, which increases the difficulty of identification. Each strand of the wire rope has multiple internal broken wires [10]. It is a difficult problem to design effective methods to identify these inner broken wires. Besides, manual feature extraction based on time-frequency analysis, such as wavelet transform and empirical mode decomposition, requires considerable expertise and has subjectivity in feature mining and selection. Therefore, it is very meaningful to investigate an automatic feature extraction method for quantitative identification of both internal and external broken wires of wire ropes.

Deep learning has been attracting considerable interest from various fields since it was introduced in 2006 [13-15]. It can extract information directly from complex raw data and automatically mine features layer by layer. Convolutional Neural Networks (CNNs) have been successfully applied as a deep learning model in the field of mechanical fault diagnosis [16, 17, 18, 19]. Janssens et al [16] proposed a CNN-based fault detection method for rotating machinery. Jing et al [17] applied CNN model to realize multi-sensor data fusion for fault diagnosis of planetary gearbox. Nevertheless, to the fault diagnosis of broken wires of wire ropes, the reports are relatively limited. The exploration is very meaningful to combine time-frequency processing method with CNN for the wire rope fault diagnosis. Thus in this paper, a quantitative identification method based on continuous wavelet transform (CWT) and CNN is proposed for the condition monitoring of wire ropes. The efficiency of the proposed method is validated by surface and internal wire-breaking experiments, which indicates that it has great potential to perform damage detection for steel wire ropes.

The main contributions of this paper are as follows:

1) A new signal processing method is proposed for the quantitative identification of broken wires. Here, the MFL signals of broken wires can be transformed to time-frequency images, without sacrificing the time-domain information and frequency-domain information. Therefore, the tedious signal processing by professionals, such as denoising and feature extraction, can be eliminated.

2) An intelligent diagnosis method for internal and external broken wires of the steel wire rope is proposed by a designed CNN. Especially, it can automatically extract and optimize the fault features of the time-frequency images. Through this operation, the accurate classification of various faults can be realized.
The remaining part of the paper proceeds as follows. In Section 2, the theory of CNN, the method of time-frequency image conversion and the designed CNN structure are introduced. Section 3 illustrates the specimen preparation and experimental settings. Section 4 presents the implementation and evaluation of the proposed method. Finally, the conclusions are drawn in Section 5.

2. Methodologies

2.1. Typical structure of convolutional neural network

There are four main ideas behind CNNs: local connection, shared weights, pooling, and the use of multiple layers [14]. Benefiting from these ideas, CNNs can achieve better results at a faster speed than conventional shallow learning models when processing large data sets.

The typical structure of a CNN is shown in Figure 1. The first few stages of the network consist of two kinds of layers: convolutional layers and pooling layers [20]. The last several levels will be the fully connected layer and a classification layer [21]. The neurons in the same convolutional layer share their weights. These weights form a convolutional kernel. Convolutional layers usually contain various convolutional kernels to extract different feature information simultaneously [22]. The convolutional kernels perform convolution calculation with the input image and put through a nonlinear activation function to form the final output value. A scan of the convolutional kernels over the whole input image generates a feature map. Convolutional kernel can be regarded as a feature extractor. Different convolutional kernels represent different feature extraction operations. Mathematically, $Z_k = W_k \ast x + b_k$ where $x$ represents the input image; $\ast$ is an operator of convolution; $W_k$ represents the convolutional kernel that generates the $k$th layer feature map, and $b_k$ is the bias value. A nonlinear activation function $\sigma(\cdot)$ is introduced to obtain the nonlinear eigenvalues $a_k$ of the $k$th feature map [17]:

$$a_k = \sigma(Z_k) = \sigma(W_k \ast x + b_k)$$ (2)

The pooling layer is typically followed by one or more convolutional layers, which can reduce the dimension of the feature maps obtained by the convolution through sub-sampling while guaranteeing the spatial invariance of the features. The pooling operation divides the feature map into multiple small regions and generates new eigenvalues, which can be expressed as [16]:

$$y_{ij,k} = \text{down}(m,n,R_{ij},x_{m,n,k})$$ (3)

where $\text{down}(\cdot)$ is the subsampling function; $y_{ij,k}$ represents the new $k$th feature map after pooling operation; $R_{ij}$ is the region near location $(i,j)$, the receptive field of the pooling; $x_{m,n,k}$ represents the neurons of the original feature map within the receptive field, its location is $(m, n)$. In general, the most commonly used pooling functions are max pooling and average pooling. The mean value of all units within the receptive field is calculated as the new eigenvalue by average pooling while the maximum value is selected as the new eigenvalue in the max pooling.

After the stacked convolutional and pooling layers, a fully connected layer usually follows to implement classification or logistic regression [23, 24]. For the classification problem, the last fully connected layer combines features learned by the previous layers to classify the image. For a regression problem, the output size must be equal to the number of response variables.

2.2. Proposed diagnosis model

As shown in Figure 2, a quantitative identification method of broken wires in steel wire ropes is proposed based on continuous wavelet transform (CWT) and CNN. It can automatically learn the fault features of the time-frequency images converted from MFL signals by building a deep network structure and realize fault diagnosis. In specific, the MFL signals of the broken wires will be firstly converted into time-frequency images. Then, the time-frequency images will be used as the input of a designed CNN for fault classification.

2.2.1. Signal-to-image conversion method

The signal processing steps of the traditional method and the proposed method are shown in Figure 3. The main function of the time-frequency analysis is to convert MFL signals of broken wires into time-frequency images. The signal processing steps of the traditional method and the proposed method are shown in Figure 3. The main function of the time-frequency analysis is to convert MFL signals of broken wires into time-frequency images.
frequency analysis in the traditional fault classification method is signal denoising and feature extraction, which usually takes a lot of energy and enough prior knowledge.

Time-frequency imaging is an effective method to represent one-dimensional oscillation signals, which can be realized by many methods [25]. In particular, the CWT is a practical approach to analyze arbitrary positions of the signal at varying scales. For this reason, the raw damage signals will be converted into images by the wavelet transform in this proposed method, which can avoid the tedious signal processing in the traditional methods.

Wavelet transform has become a widely applied time-frequency analysis method in the field of mechanical fault diagnosis [26, 27]. In this paper, it is deployed to generate the time-frequency distribution of one-dimensional MFL signals. The CWT of signal \(x(t)\) can be expressed as [26, 28]:

\[
C(a, b) = \langle x(t), \psi_{a,b}(t) \rangle = \frac{1}{\sqrt{a}} \int x(t) \psi^* \left( \frac{t - b}{a} \right) dt
\]  

(4)

where \(x(t)\) represents the signal; \(a\) is the scale, \(b\) is the translation; \(\psi(t)\) is the mother wavelet, and \(C\) is the 2D matrix of wavelet coefficients. Based on Eq. (4), one-dimensional time series can be transformed into two-dimensional images.

2.2.2. Proposed CNN structure

Followed by the raw MFL signals are converted into images, the CNN can be trained to realize the fault classification. In order to accurately identify the broken wires of the steel wire rope, a specific CNN is designed in this paper. As shown in Figure 2, the proposed CNN model based on Eqs. (1), (2), and (3) includes three convolutional layers, three pooling layers, and one fully connected layer. The convolutional and pooling layers are used to extract features from the input image, and the remaining layers are integrated for the final classification. Among them, the softmax is used to output the probability that each sample belongs to a specific class in the designed CNN model. Meanwhile, there are many activation functions in CNNs that can be chosen for a better classification of data, such as ReLU, sigmoid, etc. Here, the ReLU function is selected due to its ability to achieve fast convergence in stochastic gradient descent.

In order to facilitate fault identification, the time-domain MFL signals received by a damage detector will be transformed into the time-frequency images through CWT as the input of the CNN [29, 30]. In

![Figure 4. The locations and images of the broken wires: (a) 1 external broken wire; (b) 2 external broken wires; (c) 3 external broken wires; (d) 1 internal broken wires; (e) 2 internal broken wires; (f) 3 internal broken wires.](image-url)
Table 1. Nomenclature of broken wires.

| Label | Description |
|-------|-------------|
| 24-1  | 1 external broken wire of the 24 mm diameter wire rope |
| 24-2  | 2 external broken wire of the 24 mm diameter wire rope |
| 24-3  | 3 external broken wire of the 24 mm diameter wire rope |
| 24-4  | 1 internal broken wire of the 24 mm diameter wire rope |
| 24-5  | 2 internal broken wire of the 24 mm diameter wire rope |
| 24-6  | 3 internal broken wire of the 24 mm diameter wire rope |
| 22-1  | 1 external broken wire of the 22 mm diameter wire rope |
| 22-2  | 2 external broken wire of the 22 mm diameter wire rope |
| 22-3  | 3 external broken wire of the 22 mm diameter wire rope |
| 22-4  | 1 internal broken wire of the 22 mm diameter wire rope |
| 22-5  | 2 internal broken wire of the 22 mm diameter wire rope |
| 22-6  | 3 internal broken wire of the 22 mm diameter wire rope |
| 20-1  | 1 external broken wire of the 20 mm diameter wire rope |
| 20-2  | 2 external broken wire of the 20 mm diameter wire rope |
| 20-3  | 3 external broken wire of the 20 mm diameter wire rope |
| 20-4  | 1 internal broken wire of the 20 mm diameter wire rope |
| 20-5  | 2 internal broken wire of the 20 mm diameter wire rope |
| 20-6  | 3 internal broken wire of the 20 mm diameter wire rope |

As shown in Figure 5, the damaged wire rope is fixed to the steel wire rope test rig using the rope buckles, where a magnetic concentrating sensor is driven by the moving tray to scan the wire rope for damage detection [4]. The detection sensor can collect the MFL caused by defects through two magnetic collecting rings and two Hall elements. The test rig and sensor allow data acquisition for different sizes of broken wires and different levels of wear. The output signal of the sensor is preprocessed by a printed circuit board (PCB) and transmitted to the acquisition system (shown in Figure 6) through the cable. As can be seen from Figure 6, a DC power supplies power to the sensor and the PCB via the cables, which can ensure the circuit stability during the experiment. The MFL signals are acquired by the NI PXI-4496 card and displayed on the monitor. A LabVIEW program is designed to display and store data in real time.

4. Results and discussion

4.1. The time-frequency images transformed by CWT

The obtained oscillation signals of the damaged ropes with different diameters are shown in Figure 7, where the mutations (marked in red) corresponding to the MFL signals of the various wire breaking injuries (18 defects). Each subgraph represents six fault signals of a certain diameter. Figure 7(a) shows the damage signals of 3 external broken wires and 3 internal broken wires of the 24 mm diameter wire rope, where the 6 saltation signals correspond to six different faults in Figure 4(a)-(f) respectively. Figure 7(b) and (c) display the fault signals of wire ropes with diameter of 22 mm and 20 mm.

These MFL signals of the broken wires are separated into data segments containing 1024 data points. Each data segment is transformed into a time-frequency distribution according to Eq. (4), which is implemented in MATLAB through the “cwtfilterbank” function. Since the time-frequency distributions converted by the MFL signals are gray images with only one channel. Therefore, the two-dimensional images with three channels are obtained by channel augmentation to accommodate the two-dimensional convolution operation. The time-frequency images (RGB images) of the MFL signals of internal and external broken wires are illustrated in Figure 8. Each RGB image is an array of size 224-by-224-by-3. These time-frequency images contain the characteristic information of 18 broken wire faults. It can be seen from the converted images that there are some differences in the images of different broken wires. However, it is difficult to distinguish different kinds of defects by vision.

4.2. The parameter adjusting of the CNN model

The time-frequency images are used as the input to the intelligent network for fault classification. In the experiment, 100 samples were
Figure 7. The MFL signals of broken wires: (a) The MFL signals of broken wires of the 24 mm diameter wire rope; (b) The MFL signals of broken wires of the 22 mm diameter wire rope; (c) The MFL signals of broken wires of the 20 mm diameter wire rope.
Figure 8. The time-frequency images of MFL signals of different broken wires: (a) The time-frequency image of 1 external broken wire of the 24 mm diameter wire rope; (b) The time-frequency image of 2 external broken wires of the 24 mm diameter wire rope; (c) The time-frequency image of 3 external broken wires of the 24 mm diameter wire rope; (d) The time-frequency image of 1 internal broken wires of the 24 mm diameter wire rope; (e) The time-frequency image of 2 internal broken wires of the 24 mm diameter wire rope; (f) The time-frequency image of 3 internal broken wires of the 24 mm diameter wire rope; (g) The time-frequency image of 1 external broken wire of the 22 mm diameter wire rope; (h) The time-frequency image of 2 external broken wires of the 22 mm diameter wire rope; (i) The time-frequency image of 3 external broken wires of the 22 mm diameter wire rope; (j) The time-frequency image of 1 internal broken wires of the 22 mm diameter wire rope; (k) The time-frequency image of 2 internal broken wires of the 22 mm diameter wire rope; (l) The time-frequency image of 3 internal broken wires of the 22 mm diameter wire rope; (m) The time-frequency image of 1 external broken wire of the 20 mm diameter wire rope; (n) The time-frequency image of 2 external broken wires of the 20 mm diameter wire rope; (o) The time-frequency image of 3 external broken wires of the 20 mm diameter wire rope; (p) The time-frequency image of 1 internal broken wires of the 20 mm diameter wire rope; (q) The time-frequency image of 2 internal broken wires of the 20 mm diameter wire rope; (r) The time-frequency image of 3 internal broken wires of the 20 mm diameter wire rope.

Table 2. CNN with different parameters and various structures. (The format of the “$S_i$, $N_i$” is “filter size, filter number” of the convolutional layer and “$S_{pi}$” is “pool size” of the pooling layer. “$i$” refers to the $i$th convolutional layer or pool layer).

| Number | Architecture of CNN | Testing accuracy |
|--------|---------------------|------------------|
| 1      | 3, 6 2             | 85%              |
| 2      | 3, 8 2             | 91.11%           |
| 3      | 7, 10 2            | 93.33%           |
| 4      | 11, 12 2           | 94.44%           |
| 5      | 3, 6 2 3, 8 2      | 85.33%           |
| 6      | 7, 6 2 7, 8 2      | 93.34%           |
| 7      | 7, 6 2 7, 12 2     | 93.89%           |
| 8      | 11, 6 2 11, 12 2   | 90.56%           |
| 9      | 3, 6 2 3, 8 2 3, 8 2 | 89.44%       |
| 10     | 7, 6 2 7, 12 2 7, 12 2 | 91.11%     |
| 11     | 9, 8 2 9, 12 2 9, 12 2 | 96.11%      |
| 12     | 11, 8 2 11, 12 2 11, 12 2 | 98.15%     |

Figure 9. The accuracy-iteration graph of the selected CNN.
collected for each damage, and a total of 1800 time-frequency images were obtained. The difficulty of realizing accurate identification of broken wires lies in the establishment of an appropriate CNN model. In order to determine the optimal configuration of the CNN-based classification model for broken wires diagnosis, some parameter adjustments are undertaken. The 12 schemes with different parameters are presented in Table 2. They are employed to test a case with 18 patterns shown in Table 1, using data with 1800 sample signals, where 70% of the sample set are used for training the CNN and 30% for testing. The CNN (labeled 12 in Table 2) consisting of three convolutional layers, three pooling layers and one fully-connected layer obtains the best testing accuracy of 98.15%, which is chosen as the final model. The verification iteration diagram of the selected CNN is shown in Figure 9, and the detailed parameters of the selected model are listed in Table 3.

### 4.3. Results and comparison

Confusion matrix is an effective tool to visualize the performance of the classification models [22]. Figure 10 displays the confusion matrix using the selected CNN model for the 18 patterns listed in Table 1. The rows of the confusion matrix correspond to the actual class (Target Class) and the columns represents predicted class (Output Class). Diagonal cells correspond to correctly classified results, and non-diagonal cells correspond to incorrectly observations. The number of classifications of each pattern of the test set are displayed in each cell. From Figure 10 we can see that the vast majority of samples have been correctly identified, and only a few samples have been confused.

In addition, the proposed CNN model is compared with a backpropagation (BP) neural network. As for the BP network, some manual features such as peak value, width, area of the MFL signals, are extracted as inputs of the network [8]. A three-layer BP neural network model including an input layer, an output layer and a hidden layer is established. The number of hidden layer nodes of the BP neural network is 11. Its global percentage of classification accuracy of the 18 patterns listed in Table 1 is only 37.78%. The confusion matrix of classification results of 18 kinds of broken wires by BP network is shown in Figure 11. Looking at Figure 11, it is apparent that there is a serious confusion between different types of fault samples. The classification accuracy of each fault using BP network and CNN is shown in Figure 12. It can be seen from Figure 12 that the recognition effect of the proposed method for each fault has been greatly improved. Compared with the traditional BP network, the identification model of broken wires of wire ropes based on proposed CNN has superior performance.

In order to further analyze the performance of the designed CNN, the t-distributed stochastic neighbor embedding (t-SNE) is used to realize the dimensionality reduction and visualization of broken wire features [31, 32]. The activation of each observation in the dataset is computed in the early convolutional layer, the final convolutional layer and the final softmax layer. Then the two-dimensional representations of the data in these layers is calculated using the t-SNE algorithm, which is displayed in Figure 13. It can be seen from Figure 13 that after processing by several convolutional layers, the clustering of the broken wire features becomes more and more obvious, and finally an accurate distinction is achieved in the softmax layer.

The artificial features in BP network visualized using t-SNE algorithm are shown in Figure 14. Compared with the feature clustering of the designed CNN, these artificial features have serious confusion, which is not conducive to the identification of various types of broken wires. This result further demonstrates the excellent performance of the proposed CNN for the quantitative identification of broken wires.

| Layer | Type       | Variables            | Training parameters                        |
|-------|------------|----------------------|--------------------------------------------|
| 1     | Convolutional layer | Filter Size: 11 | Solver: adam                               |
|       |            | NumFilters: 8       | Initial Learn Rate: 0.001                   |
|       |            |                      | Validation Frequency: 21                   |
|       |            |                      | Max epochs: 12                              |
|       |            |                      | Mini Batch Size: 20                        |
|       |            |                      | Execution Environment: cpu                 |
| 2     | Pooling layer | Pool Size: 2       |                                            |
| 3     | Convolutional layer | Filter Size: 11 |                                            |
|       |            | NumFilters: 12      |                                            |
| 4     | Pooling layer | Pool Size: 2       |                                            |
| 5     | Convolutional layer | Filter Size: 11 |                                            |
|       |            | NumFilters: 12      |                                            |
| 6     | Pooling layer | Pool Size: 2       |                                            |
| 7     | Fully connected | 18 outputs          |                                            |
Conclusions

In this paper, an intelligent fault diagnosis method based on CWT and CNN is proposed for quantitative identification of broken wires of steel wire ropes. The raw damage signals are converted into time-frequency images by the CWT algorithm, which can avoid the tedious signal processing in the traditional methods. With a designed CNN, the internal and external broken wires can be accurately identified. In order to evaluate the performance of the proposed method, the broken wires diagnosis experiments were carried out using different wire ropes. The results demonstrate that the proposed method has a very superior performance for quantitative identification of broken wires with the recognition accuracy of 98.15%, comparing to the traditional BP method with the recognition accuracy of 37.78%. This model has great potential in the application of condition monitoring for steel wire ropes.

Although the proposed CNN model shows excellent performance in the classification of external broken wires and inner breaks close to the...
surface, we have not tested its classification effect for deeper broken wires. For the real industry application of our model, more experiments should be researched under various working conditions to realize the generalization of the model. In addition, it is urgent and essential to evaluate the CNN-based model comprehensively with different kinds of faults of wire ropes in the future work.

Declarations

Author contribution statement

Yiqing Zhang: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Zesen Feng; Sui Shi; Zhihu Dong: Performed the experiments.
Ling Zhao: Analyzed and interpreted the data.
Luyang Jing: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.
Jiwen Tan: Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of interest’s statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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