Damage identification of wire rope under noise background via Light- EfficientNetV2 and Magnetic flux leakage image

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Abstract

Magnetic flux leakage (MFL) testing, non-destructive testing, can prevent some major accidents of hoist equipment by identifying the damage of wire ropes. However, in harsh working conditions such as mines and oil wells, the inevitable vibration and swing of wire rope will generate noise and interfere with the MFL signal, which makes us difficult to identify the damage. As a classification network, Convolutional neural network (CNN) is positive in recognition accuracy and noise resistance, but it hardly uses in wire rope damage classification. To improve the accuracy of wire rope damage identification under noise background, we propose a method of wire rope damage identification via Light-EfficientNetV2 and MFL image. First, the MFL signal is segmented and rearranged to form the MFL image, and then the image is classified by Light-EfficientNetV2. To improve the classification efficiency, we reduce the layers of EfficientNetV2 to make it lighter. Finally, the availability of this method is proved by the validation set. Compared with four neural networks, the accuracy is the highest. Moreover, as the noise increased, the accuracy of Light-EfficientNetV2 is higher than EfficientNetV2, which has application value in the wire rope damage identification under noise background.

1 Introduction

Wire rope is used for lifting, pulling, tensioning, and bearing in material handling machinery. It has many advantages such as high strength, light deadweight, and stable operation. However, the working environment of the wire rope is harsh, and it is prone to wear, breakage and other damages in use. Once the wire rope is damaged, it will affect its bearing capacity, which is easy to break and causes economic losses and casualties. Therefore, it is significant to implement damage detection for wire rope.

There are many non-destructive testing methods for wire ropes, including ultrasonic testing [1], radiographic testing [2], electromagnetic testing [3], etc. MFL testing is non-destructive testing with high efficiency and reliability, which comprehensively detects the internal and external defects of ferromagnetic materials [4, 5]. This testing method is suitable for wire rope inspection [6, 7]. The detection principle is to conduct axial magnetization of the wire rope through DC coils or permanent magnet instruments, detect the MFL at the damaged part through the Hall sensor and output the MFL signal. According to the MFL signal, the damage type of the wire rope can be determined.

The MFL signal under dreadful working conditions is interfered with by noise, and it is difficult to recognize the damage. To deal with the damage identification of the MFL signal under noise background, many scholars have done relevant research work. Among them, Shan et al proposed an adaptive shift average algorithm method to denoise the MFL signal [8]. They found the optimal window width matrix through iterative optimization and obtained a high signal-to-noise ratio. Yao et al. conducted denoising processing based on wavelet multi resolution analysis methods, and effectively eliminated abnormal points, power frequency interference, and background noise through feature decomposition and reconstruction of broken wire damage signals [9]. The method suppresses the strand-waveform noise
and highlights the signal. The above methods can denoise the MFL signal, but they cannot intelligently find the damage.

With the development of machine learning, quick identification and classification are deeply concerned by scholars in fault diagnosis [10–14]. At the same time, the combination of the denoising method and machine learning provides a new direction for wire rope damage identification. Zhang et al conducted wavelet denoising for the MFL signal of the wire rope [15]. Then they conducted damage classification and feature extraction in space, and finally input the features into a wavelet neural network for damage identification. Kim and Park used Hilbert transform to denoise and quantified the MFL signal by using the damage indexes [16]. Then they used an artificial neural network to automatically estimate the severity of the damage. These methods have high accuracy for the identification of the wire rope damage under noise background. However, signal denoising and eigenvalue extraction are complex and tedious. It is very necessary to find a method that combines machine learning with damage identification without denoising and feature extraction.

CNN in machine learning has fast speed, high accuracy, and good robustness for image classification [17–19], so it is widely used in fault identification and classification [20–22]. Some scholars use the characteristics of CNN to convert the damage signals in the fault field into images and input them into CNN for damage identification. Chen et al fused the horizontal and vertical vibration data of the gearbox into a two-dimensional matrix and used DCNN to identify the health of the gearbox [23]. Sun et al transformed the 1D fault signals of the gas sensor into 2D gray images and used the CNN to improve the accuracy of fault diagnosis of hydrogen sensors [24]. Yang et al converted the multi-source vibration signal into a two-dimensional matrix and used CNN for fault diagnosis of reciprocating compressors [25]. At the same time, CNN also has a certain noise resistance. Hoang et al proposed a rolling bearing fault diagnosis method based on CNN. They converted vibration signals into images. Without denoising, it effectively classified damage in noisy background, and had certain robustness and fault tolerance [26]. EfficientnetV2, as a newly proposed classification network, increases the network width, depth, and resolution to improve the performance [27, 28]. It has been used in plant disease detection [29, 30], mechanical fault diagnosis [31], and some other fields [32, 33].

Compared with the signal, the image will be more intuitive. Many scholars are committed to finding the conversion relationship between the MFL signal and the MFL image and observing the damage more intuitively through the MFL image. For example, Li et al and Zheng et al both obtain multiple MFL signals through multiple Hall sensor arrays and the obtained numerical matrix forms the MFL image [34, 35]. However, multiple MFL signals to MFL images require a large amount of computation. It is necessary to transfer the single MFL signal to the MFL image. Inspired by the transformation of the bearing vibration signal into the image signal [36–38], the MFL signal is preprocessed by wavelet transform and array segmentation to form a numerical matrix, and the numerical matrix is transformed into the image. Compared with the bearing vibration signal, the MFL signal is mostly the pulse signal or the abnormal amplitude signal, which makes it easier to see the damage of the wire rope in the MFL image.
Previous studies of denoising and machine learning have been able to identify the damage of the wire rope. However, the denoising and feature extraction for MFL signals are complicated, and it is also unable to combine CNN with higher classification accuracy. To deal with the problems, we propose a method of wire rope damage identification via Light-EfficientNetV2 and MFL image. The overall flow chart is shown in Fig. 1. Firstly, the MFL signal of the wire rope under noise background is segmented to form a numerical matrix and then turn into an MFL image. Then, the Light-EfficientNetV2 is selected in the CNN, which reduces the number of layers and accelerates the training efficiency. Finally, the obtained images are divided into the training set and the verification set and then brought into the network for damage identification.

This paper is arranged as follows: Section 2 introduces the principle of MFL testing, the characteristics of the noise, and the test rig. Section 3 transforms the MFL signal to the MFL image. Section 4 presents the Light-EfficientNetV2 network and the training results for MFL images. The last section gives the conclusion of this paper.

2 MFL Testing

In this part, the principle of MFL testing, the characteristics of the noise, and the test rig will be mainly introduced.

2.1 MFL testing

At present, MFL testing is commonly used in the research of wire rope damage detection. The wire rope has the property of high magnetic permeability, and the permanent magnet is used to magnetize the wire rope. When the wire rope is damaged, the magnetic resistance increases and the magnetic flux decreases at the damaged position. Then, the magnetic leakage occurs and reflects in the MFL signal. The damage is judged by detecting the MFL signal.

The MFL detector is mainly composed of permanent magnet, soft magnetic material, air gap, etc., as shown in Fig. 2(a). When there is damage such as broken wire or wear, the magnetic line of force refracts from the defect, and the Hall array around the measured rope section can sense this leakage magnetic field. Finally, the MFL signal can be preprocessed to extract effective damage signal. According to the principle of MFL detection, the caaKEr flaw detector is selected to collect the damage signal. The structure of the flaw detector is shown in Fig. 2(b).

2.2 Noise characteristics

The working environment of the wire rope is harsh, and the vibration, circuit elements and magnetic field of the wire rope will generate random noise, which is inevitable and easy to submerge the damage signal, affecting the final detection result. Therefore, the noise interference under this working condition is usually regarded as Gaussian white noise, which is difficult to ignore. In this paper, Gaussian white noise
\[ N(t) = \sqrt{2D} \xi(t) \cdot N(t) \]

represents Gaussian white noise, \( D \) represents noise intensity, \( \xi(t) \) is the standard white Gaussian noise with the mean value of 0 and variance of 1, and \( \delta(t) \) represents the Dirac function with the mean of 1. The MFL signal with different Gaussian white noise is shown in Fig. 3.

### 2.3 Test rig

We set up a test rig for damage detection of wire rope, mainly consisting of a caaKEr flaw detector, sample wire rope (6 × 37S-FC, the wire rope has 6 strands, 37 wires per strand. The rope core is hemp core, with a diameter of 39 mm), tensioning device, and support device. The test rig is shown in Fig. 4. Herein, the caaKEr flaw detector is used to conduct flaw detection on the wire rope, and the flaw detector is pushed to crawl on the sample wire rope. The flaw detector acquisition device is used to collect the MFL signal and display it on the laptop.

### 3 MFL Signal To MFL Image

The method of converting the MFL signal to the MFL image is shown in Fig. 5. Time-domain signal can be converted to images in the desired \( M \times N \) dimensions. The size of the image can be adjusted to the desired length according to the length of the signal. First, the MFL signal is divided into samples with a specific length of sampling points. Then, the sample matrix is formed through sample arrangement. Finally, the normalized sample matrix is converted to the MFL image. The dimensions of the image should be within the dimensions of meaningful expressions. For the convenience of subsequent in-depth learning, the MFL signal is converted to 256 × 256 MFL image in the following conversion.

As the working time increases, there will be many different damages of the wire rope. MFL testing is mainly aimed at local damage, mainly broken wire. Among the MFL signals of broken wire collected in the test rig, the damages are characterized by the sudden reduction of the metal sectional area, which are reflected in the MFL signals as shown in Fig. 6 (a) and (c). The MFL signals are transferred to MFL images shown in Fig. 6 (b) and (d). The damaged parts are represented by red boxes. By observing the MFL images, we can see the damaged parts intuitively.

In the working site, the MFL signal of a broken wire is composed of strand wave signal, broken wire source signal, and noise signal. We add Gaussian white noise to the MFL signals in Fig. 6 (a) and (c), as shown in Fig. 7 (a) and (c). The MFL signals under noise background converted into MFL images are shown in Fig. 7 (b) and (d). The damaged parts are represented by red boxes. It can be seen that the
damage characteristics are submerged by noise in the MFL signals. However, the damage can still be seen in the MFL images.

The wear of wire rope is characterized by the general reduction of metal sectional area in a long range. Its MFL signal under noise background is shown in Fig. 8 (a), and it is shown in Fig. 8 (b) after being converted into MFL image. The damaged part is shown in red box. The damage can also be clearly seen from the MFL image.

4 Light-efficientnetv2 Training And Verification

In this part, the structure of Light-EfficientNetV2 and the training results will be mainly introduced.

4.1 Introduction of Light-EfficientNetV2 Network

In classification networks, the width, depth, and the resolution are the key parameters to improve the network performance. Some classification networks only consider one parameter, but it cannot achieve great performance. In EfficientnetV2, the above parameters will all be increased to improve the network performance.

Considering the training efficiency, we adopt the structure of EfficientNetV2-S, as shown in Table 1. We can see that EfficientNetV2-S is divided into Stage0 to Stage7. Conv3x3 consists of a 3x3 convolution, activation function, and BN. k3x3 represents the size of the convolution kernel

<table>
<thead>
<tr>
<th>Stage</th>
<th>Operator</th>
<th>Stride</th>
<th>#Channels</th>
<th>#Layers</th>
</tr>
</thead>
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<tr>
<td>0</td>
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<td>2</td>
<td>24</td>
<td>1</td>
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<tr>
<td>1</td>
<td>Fused-MBConv1, k3×3</td>
<td>1</td>
<td>24</td>
<td>2</td>
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<tr>
<td>2</td>
<td>Fused-MBConv4, k3×3</td>
<td>2</td>
<td>48</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>Fused-MBConv4, k3×3</td>
<td>2</td>
<td>64</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>MBConv4, k3×3, SE0.25</td>
<td>2</td>
<td>128</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>MBConv6, k3×3, SE0.25</td>
<td>1</td>
<td>160</td>
<td>9</td>
</tr>
<tr>
<td>6</td>
<td>MBConv6, k3×3, SE0.25</td>
<td>2</td>
<td>256</td>
<td>15</td>
</tr>
<tr>
<td>7</td>
<td>Conv1×1&amp;Pooling&amp;FC</td>
<td>-</td>
<td>1280</td>
<td>1</td>
</tr>
</tbody>
</table>

The structures of Fused MBconv and MBConv are shown in Fig. 9. Fused MBconv replaces the expansion conv1x1 and depthwise conv3x3 in the branch of the MBConv structure with a common conv3x3. Replacing the shallow MBConv structure with the Fused MBConv structure makes full use of the existing accelerator and significantly improves the training speed.
The SE module makes the network fix on the important parts, as shown in Fig. 10. It consists of an average pooling and two full connection layers. The number of nodes in the first full connection layer is equal to 1/4 of the input MBConv channels. The number of nodes in the second full connection layer is equal to the output Depth Conv channels.

In the EfficientNetV2-S structure, the number of hidden layers in each layer is 2, 4, 4, 6, 9, and 15 respectively. However, the number of hidden layers will affect the training efficiency, resulting in over-fitting of training and low accuracy of verification set. In EfficientNetV2-s, the number of hidden layers can be further reduced. Therefore, we half the number of hidden layers. Now the number of hidden layers in each layer to 2, 2, 2, 3, 5, and 8, as shown in Table 2. Compared with the original network structure, the Light-EfficientNetV2-S improves the efficiency of training.

<table>
<thead>
<tr>
<th>Stage</th>
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<th>#Channels</th>
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<td>Fused-MBConv4, k3×3</td>
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<td>4</td>
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<td>2</td>
<td>128</td>
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<tr>
<td>5</td>
<td>MBConv6, k3×3, SE0.25</td>
<td>1</td>
<td>160</td>
<td>5</td>
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<td>6</td>
<td>MBConv6, k3×3, SE0.25</td>
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<td>256</td>
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<td>7</td>
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<td>-</td>
<td>1280</td>
<td>1</td>
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</table>

### 4.2 Damage identification process

The acquisition of MFL signal will be affected by lift off value and detection speed, and the MFL signal obtained by each detection will be different, which is conducive to building the damage database. We selected 3 broken wire damages on the wire rope and obtained multiple groups of MFL signals by repeatedly dragging the flaw detector. Then we add Gaussian white noise with $D = 10$ to each group of signals, and take no damage, one damage, two damage and three damage as the classification criteria. The damage signals are segmented by different window widths, and then converted into MFL images, which are labeled. Repeat the above steps to obtain 500 MFL images of no damage, one damage, two damage and three damage respectively, divide them into training set and verification set at 8:2, bring them into Light-EfficientNetV2 for training. The training model is 30 and take the best one-time training model to verify with verification set.

We use the EfficientNetV2 to train the MFL image, and the training results are shown in Fig. 11 (a) and (b). There is a high recognition rate in the graphic classification of no damage, one damage, and two
damages, while the recognition rate of three damages is low, and the total accuracy rate is 98.5%. Then we use the Light-EfficientNetV2 to train the MFL image. The training results are shown in Fig. 11 (c) and (d). The recognition rate of three damages is improved, with a total accuracy of 99.8%. The EfficientNetV2 has an overfitting phenomenon for identifying the MFL images. By reducing the number of hidden layers, the network structure is lighter and the recognition efficiency is higher.

To further illustrate the advantages of the method, we compare four neural networks: the ResNet [39], the GoogleNet [40], the AlexNet [41] and the EfficientNetV2. As shown in Table. 3, the accuracy of the proposed method is the highest. The comparison results show that the method proposed in this paper can accurately identify damage in noise background. Meanwhile, other neural networks also have high accuracy, indicating that the method of using MFL images to identify damage is universal.

<table>
<thead>
<tr>
<th>Neural Networks</th>
<th>Recognition accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>97%</td>
</tr>
<tr>
<td>EfficientNetV2</td>
<td>98.5%</td>
</tr>
<tr>
<td>Light-EfficientNetV2</td>
<td>99.8%</td>
</tr>
<tr>
<td>ResNet</td>
<td>99.5%</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>99.5%</td>
</tr>
</tbody>
</table>

**Table 3**
The accuracy of five neural networks in $D = 10$

### 4.3 Damage identification process under stronger noise background

To verify the effectiveness of the proposed method under stronger noise background, we enhance the noise to $D = 20$ and $D = 40$, generate 500 MFL images of no damage, one damage, two damage, and three damage, and train them with EfficientNetV2 and Light-EfficientNetV2 respectively. The accuracy of EfficientNetV2 and Light-EfficientNetV2 respectively is shown in Table. 4. It has been verified that Light-EfficientNetV2 has higher recognition accuracy and better anti-noise ability for MFL images.

<table>
<thead>
<tr>
<th>Neural Networks</th>
<th>D = 20</th>
<th>D = 40</th>
</tr>
</thead>
<tbody>
<tr>
<td>EfficientNetV2</td>
<td>93.6%</td>
<td>90.5%</td>
</tr>
<tr>
<td>Light-EfficientNetV2</td>
<td>96.8%</td>
<td>91.7%</td>
</tr>
</tbody>
</table>

**Table 4**
The accuracy of EfficientNetV2 and Light-EfficientNetV2 respectively in $D = 20$ and $D = 40$.

### 5 Conclusion
In this paper, aiming at the problem that the MFL signal is difficult to identify the damage of wire rope under noise background, a damage identification method via Light-EfficientNetV2 and MFL image is proposed. Firstly, the one-dimensional MFL signal of wire rope under noise background is segmented. Then, the numerical matrix is transformed to the MFL image. The MFL images of the damage are corresponding to the number of broken wires, labeled, and divided into the training set and the verification set. Finally, Light-EfficientNetV2 is trained with the training set, and the best training model is used to test the verification set. The accuracy rate in noise background is higher, which solves the problem of damage identification of wire rope in noise background. The method is also applicable to the damage identification of wire rope in other workplaces. The main conclusions of this paper are as follows:

(1) The method of transferring the MFL signal to the MFL image is proposed. The damage can be observed more intuitively through the image.

(2) Using Light-EfficientNetV2 to train and classify MFL images, it is not necessary to denoise and extract feature in advance, which has the advantages of noise resistance and high recognition accuracy.

(3) To prevent overfitting of training, Light-EfficientNetV2 reduces the number of hidden layers. Compared with the EfficientNetV2, the Light-EfficientNetV2 has higher accuracy in MFL image recognition.

Declarations

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Author Contributions


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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Ethical Approval and Consent to Participate**

The authors have read and understood the publishing policy, and submit this manuscript in accordance with this policy.

**Consent for Publication**

Not applicable.

**References**


**Figures**
Figure 1

Overall flow chart of wire rope damage identification
Figure 2

The MFL detector

Figure 3

The MFL signal with Gaussian white noise. (a) The pure MFL signal. (b) The MFL signal with Gaussian white noise, $D=10$. (c) The MFL signal with Gaussian white noise, $D=20$. (d) The MFL signal with Gaussian white noise, $D=40$. 
Figure 4

The test rig, consisting of a caaKEr flaw detector, sample wire rope tensioning device, and support device.
Figure 5

Overall plan of MFL signal to MFL image
Figure 6

Test rig acquisition of MFL image of broken wire signal. (a) and (c) The MFL signals of broken wire collected in the test rig. (b) and (d) The corresponding MFL images
Figure 7
MFL image of broken wire signal under noise background. (a) and (c) The MFL signals under noise background. (b) and (d) The corresponding MFL images under noise background.

Figure 8
MFL image of wear under noise background. (a) The MFL signals under noise background. (b) The corresponding MFL images under noise background.

Figure 9
MBConv structure and Fused MBConv structure
Figure 10

The SE module

Figure 11

Network training results in $D=10$. (a) and (b) The EfficientNetV2 network training results. (c) and (d) The Light-EfficientNetV2 network training results.