Defect detection for aluminium conductor composite core X-ray image with deep convolution network

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Abstract. The Aluminum Conductor Composite Core (ACCC) has been considered one of the solutions for massively increasing requirements for the electricity power transmission in China due to its superiority in weight, strength and ampacity. Yet the popularize of ACCC lines suffer from damages caused during the construction, which may result in line broke in the future. In this paper, an automatic defect detection method based on Deep Convolution Network is proposed. Image classification framework with Inception-Resnet structure as backbone is applied. With the online self-designed robot, the proposed method can effectively detect the defects such as fracture, splitting and distortion, with a recall rate over 90%.

1. Introduction

The Aluminium Conductor Composite Core (ACCC) wire, which is now partially used in high-voltage power grids, has become the most promising type of wire due to its properties such as light weight, large current capacity, low line loss, and small sag. It is one of the solutions to the rapid increasing requirement on the electricity resource in China.

Although ACCC is known for its superiority in transmission performance, its poor bending resistance has become the major obstacle to its application. Collisions and bending during construction may result in damage to the ACCC, which may further cause damage to the cable. Since the carbon core is tightly wrapped inside the metal, and the defect scale is small, methods such as stress detection [1-2], electromagnetic induction detection [3-4] and sound wave detection [5-6] are not available for online detection. X-ray imaging, which is widely used in non-destructive testing in recent years [7-10] provide us possibility of observing inside damage to the cable.

However, in X-ray imaging, the outer steed core absorbs most of the energy and the contrast of carbon core area is with low contrast, therefore, some of the defects are hard to distinguish (See Figure 1). Besides the difficulty in observation, the online detection on overhead lines requires fast and continues detection for large amounts of images, which is stressful job for human workers. The poor visualization of the defects and the huge data for processing become the main limitation to automatic non-destructive testing for ACCC wires. The object classification and detection algorithm represented by RCNN method [11-14] has been widely used in the field of non-destructive testing [15-21]. Although such methods can process large amounts of images rapidly, the automatic damage detection is still rather challenging due to the poor contrast of the images.

In this paper, a robust defect detection method based on Deep Convolution Neutral Network (DCNN) is proposed, histogram matching [22] is considered as normalization step so as to reduce the
deviation of samples, and thus improve defect detection efficiency and accuracy. Instead of object detection framework, image classification network is applied here, because the location of the defects is always in the middle of the cable. The ACCC images are separated into overlapped small patches, and the proposed network aims to find out the patches with defects. The experimental results indicate that the proposed methods can effectively detect the defects such as fracture, splitting and distortion, with a recall rate over 90%.

![Complete ACCC defect](image1.png) ![Enlarged defect image](image2.png)

**Figure 1.** Defects that hard to distinguish.

2. **Data acquisition and pre-processing**

2.1. **Acquisition system**

A crawling robot is designed for image acquisition (See Figure 2). The robot climbs on the ACCC, X-ray scanning to conducts image acquisition and image preprocessing, and transmits the image to the upper computer through WIFI graphics transmission, at last the upper computer carries out defect detection.

![Data acquisition robot](image3.png)

**Figure 2.** Data acquisition robot.

![Detection flow chart](image4.png)

**Figure 3.** Detection flow chart.

As is shown in Figure 3, the image acquisition is completed with a crawling robot designed by the school of instrument science and engineering of Southeast University. While working, the robot climbs on the ACCC, uses X-ray scanning to conducts image acquisition and image preprocessing, and transmits the image to the upper computer through wifi graphics transmission, at last the upper computer carries out defect detection.

A crawling robot is designed for image acquisition. The robot is designed by the school of instrument science and engineering of Southeast University, as shown in Figure 1. It consists of a visor, gears, power supply and imaging equipment, weighs 25 kg and runs at 0.2 m / s with an X-ray source rated at 120 kEV and 1 mA. In more detail, the X-ray detector model is PerkinElmer XRpad2 with a resolution of 100 microns. The lower computer is integrated on the robot, with ARK1123H small industrial control system, and the CPU is the Intel Celeron J1900, which it is responsible for image acquisition and partial preprocessing. The upper computer is a Dell G7 laptop, the CPU is a Core i7, and the graphics card is NVIDIA 2070Max-Q, which is responsible for image normalization, image enhancement and real-time detection operations.
2.2. Image pre-processing

As shown in Figure 4, the pre-processing process includes Segmentation and straightening and Grey level normalization, this process ensures the consistency of the training map in position and gray distribution.

![Figure 4. Preprocessing flow chart.](image)

2.2.1. The image segmentation and straightening. Due to the effect of gravity, the ACCC is not horizontally straight in the image, straightening and thresholding is required to extract straight ACCC lines, so as to ensure the position of ACCC is fixed in each image. For straightening, we use the coordinates of center pixels on ACCC for each vertical line as reference, translation is done for every vertical line according to each vertical offset (See Figure 5).

![Figure 5. Segmentation and straightening.](image)

2.2.2. Grey level normalization. The normalization of brightness and contrast is also included in the pre-processing step. The inconsistency in the images involves 2 aspects: Brightness inconsistency in single image and contrast inconsistency between different images (See Figures 6 and 7). Brightness inconsistency in the horizontal direction is caused by varied X-ray incident angle and detector plane response, which results in the defects to have different appearance in different positions; the contrast inconsistency in different images leads to different defects contrast in different images.

![Figure 6. Illustration of normalization: (the left side is the original images, the middle is the reference image, and the right side is the normalized images).](image)
For inconsistent brightness in the horizontal direction, compensation is applied according to vertical integration. To avoid discontinuities, we replace vertical integration with vertical template convolution. For contrast inconsistency in different images, histogram specification is considered to ensure uniform color distribution.

Figure 7. Single image normalization.

3. Detection network

Instead of object detection framework [23], we choose to use image classification network for our case (See Figure 8). There are two reasons. First, the dark twills among steel cables sometimes coincide with defects, therefore, the defects are difficult to distinguish for object detection networks. Second, the frequently used object detection frameworks are currently separated into two categories: two stage networks and one stage networks. The two stage ones are generally known to be with higher detection accuracy, yet the region proposal stage is relatively time consuming; for one stage methods, the regression step also requires extra computation.

Figure 8. Network structure diagram.

In our problem, since the defect location is determined in the ACCC (near the center), once the input ACCC image size is fixed, the defect detection can be easily processed via classification network. The ACCC lines are separated into small patches with overlap, we only have to figure out whether defect is contained in the patch. Figure 9 is the schematic diagram of the cutting process, all the patches are with constant size. The patches are with overlap, as shown in Figure 9 (blue and yellow boxes), so as to prevent that the defects appear near the patch border. Since the gap of the outer aluminum wire will produce interference dark stripes, which may be recognized as defects by the classifier, the patches in our proposal contains only carbon core area.

We use Inception-resnet-v2 for feature extraction network, as shown in Figure 10. Compare to the original network, the down-sampling layer is removed because the patches are with fixed size and resolution. The number of convolution layers is also reduced.
Figure 9. Patch selection.

Input \(128 \times 128 \times 1\)

\[\begin{array}{c}
\text{stem} \\
5 \times \text{inception-resnet-A} \\
\text{Reduction-A} \\
10 \times \text{inception-resnet-B} \\
5 \times \text{inception-resnet-C} \\
\text{Average Pooling} \\
\text{Dropout} \\
\text{Softmax}
\end{array}\]

(a) Inception-Resnet-v2

(b) Stem

(c) Inception-Resnet-A

(d) Inception-Resnet-B

(e) Inception-Resnet-C

(f) Reduction

Figure 10. Detection network.
3.1. Dataset and settings

According to the morphological features of defects, there are 3 kinds of defects: bending, saw and gap (See Figure 11). Among all defect samples, crease is with the most frequency.

There are totally 1617 original images obtained, due to the insufficient defect samples, we separate the dataset into train set (1000), validation set (308) and test set (307), data augmentation is performed separately via translation, flip, rotation, smoothing, noise simulation and contrast adjustment. Finally, we get 65,057 samples, among which 39,477 are training samples and 15,580 are validation samples, and the other are test samples. (sample size 128×128×1). Because the detection accuracy of multiple classification is the same as that of binary classification, during training, as shown in Table 1, the samples are separated into two categories, defect and no defect.

| Category   | learning rate | batch size | training times(epoch) |
|------------|---------------|------------|-----------------------|
| 2          | 0.0001        | 64         | 20                    |

(a) No defect  
(b) Bending  
(c) Saw  
(d) Gap

Figure 11. Sample type.

3.2. Training results

The size of each patch is set to 128×128. Four kind of networks, including Resnet-v2-50, Resnet-v2-101, Resnet-v2-200, Inception-resnet-v2 are considered in our experiment as backbones. including Resnet-v2-50, Resnet-v2-101, Resnet-v2-200 [24], Inception-resnet-v2 [25]. Comparison of test results between resnet network and Inception-resnet-v2 network:

Figure 12. Accuracy of validation set.
As shown in Figure 12, in terms of convergence speed, resnet-v2-50 and inception-resnet-v2 has a similar convergence speed, while resnet-v2-101 and resnet-v2-200 have a similar convergence speed, the latter is faster. In terms of accuracy, the precision of resnet-v2 models are similar, while the precision of inception-resnet-v2 network is the higher than the other three models. Comprehensively, since the convergence speed is not much different, while the accuracy of inception-resnet-v2 is higher, thus inception-resnet-v2 is the best choice for the model.

3.3. Results

3.3.1. Test set detection analysis. In Table 2, it can be seen that although the accuracy and recall rates of four models are close to each other in the validation set, the inception-resnet-v2 still the has the best detection result, which is once again proved to be the best choice.

| Model         | Accuracy | Recall  |
|---------------|----------|---------|
| Proposed      | 95.41%   | 90.91%  |
| Resnet-v2-50  | 94.58%   | 89.87%  |
| Resnet-v2-101 | 94.00%   | 88.34%  |
| Resnet-v2-200 | 94.06%   | 88.89%  |

3.3.2. Grey level normalization comparative analysis. Apparently, normalization step can significantly improve the recall rate and accuracy of data according to Table 3. This is because the normalization makes the overall contrast distribution of all detected samples similar, and the solution of defect features is limited to a smaller sample space, which greatly reduces the number of samples required during training, accelerates the training process, and improves the accuracy.

|                | Accuracy | Recall  |
|----------------|----------|---------|
| Grey level normalization | 95.41%   | 90.91%  |
| Unprocessing    | 81.85%   | 82.43%  |

3.3.3. Abnormal situation analysis. As is shown in Figure 13, It can be concluded that the missed detection mostly occurs when the defect is visually inconspicuous or near the edge of the patch. When the defect is visually inconspicuous, it is difficult to extract and characterize the defect feature. The defects that too close to the edge are also hard to detect because our network mainly focus on the defects in the patch center, this can be prevented by properly set overlay ratio to the patches.

![Figure 13. Abnormal condition.](image)

False detection occurs when the quality of the detected image is poor, such as too much noise in the image, or when a minor defect in the training set is similar to passing a higher level.
4. Conclusions
Defect Detection for ACCC is a new job, and no one has done it before, so this work is not compared with previous work in this paper. The main contribution of this paper is to use the convolutional neural network to better solve the problem of difficult to detect defects in the ACCC, and to have a good real-time detection ability, which can meet the requirements of field inspection.

In this deep convolutional network is applied to detect defect in ACCC. Preprocessing operations such as straightening, cropping and gray normalization are considered to ensure the accuracy of defect detection. According to the experimental results, the defect detection recall rate of this detection network reaches 90.91%. The normalization step greatly reduced the time cost for training. In our case, the training cost only about 2 hours. The detection speed for each patch is about 8.3ms, and about 0.3s for each cable image, which indicates that the proposed method reaches the requirement for real-time detection.

To improve the detection accuracy and reduce the amount of abnormal situation analysis, defect data augmentation will be considered. By generating more defect data with more morphologies, we can further improve the detection accuracy and increase the generalization of the model.

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