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Identification Methods for Structural Problems of Bridges Based on Deep Convolutional Neural Network

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The safety of bridges, which are key components of roads, has attracted the attention of experts, technical engineers, and maintenance managers. Various apparent problems such as cracks, voids and pits, white precipitate, and corrosion must be identified during the visual inspection of a bridge. In this study, using soft-nonmaximum suppression (NMS), we improved the original NMS algorithm of the faster regional convolutional neural network (Faster R-CNN) and built a fine identification network model to classify and identify the structural problems of bridges to effectively reduce the missed detection rate. In addition, through manual inspection by photography, the average accuracies of the identification of problems, namely, voids and pits, cracks, and white precipitate, can reach 80.86, 81.42, and 87.39%, respectively, which are about 20 percentage points higher than that of the original Faster R-CNN.

1. Introduction

Administrative and maintenance departments usually check bridges regularly and identify whether problems such as cracks, crack damage, exposed reinforcement corrosion, and bearing separation in the main member of the bridge are present through conventional identification methods with the naked eye or auxiliary tools such as a bridge-detection vehicle and a telescope. However, in the bridge structure, there are many places that are difficult for humans or bridge-detection vehicles to reach, and there are certain safety risks during the identification process. In addition, with the development of aerial photography and remote sensing technology, better and newer technologies are applied to the acquisition of apparent bridge images. For example, the overall scan of the appearance of bridge structures has been used in engineering practice by means of unmanned aerial vehicles,(1) wall climbing robots,(2) and noncontact instruments.(3) With such a development trend, manual inspection through photography by collecting images of problems will be replaced by machine learning and deep learning methods for the automatic identification of the type, size, and location of problems, which means that the identification of

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bridge problems becomes smarter, more convenient, and more accurate, significantly reducing the workload and the working hours involved in manual inspection.[4]

In China, with the rapid development of computer performance and artificial intelligence technology, deep learning and other techniques have been widely applied in the field of bridge structure damage recognition.[5] For instance, researchers have examined the application of deep convolutional neural networks (CNNs) in the classification and recognition of bridge structure surface defects, categorizing bridge damages into three main types: cracks, corrosion, and defects.[6] Through the use of transfer learning techniques and the training of the AlexNet CNN, an automatic recognition model for bridge surface damages was constructed. This model has demonstrated a high accuracy rate (AP) in practical applications, making it suitable for the rapid identification of bridge surface damages.[7] Additionally, another study proposed a bridge damage detection and recognition method based on deep CNNs, which includes creating a database of annotated and labeled images, training neural networks for preliminary and detailed damage selection, and cross-training, all aimed at enhancing the accuracy and robustness of bridge damage recognition.

Internationally, significant progress has also been made in the research of bridge structure damage recognition. For example, some scholars have used multilayer neural network methods to study an expert evaluation system for deteriorated prestressed concrete bridges, advancing the evaluation of deteriorating concrete bridges.[8] Moreover, various methods for assessing the health status of bridges, such as fuzzy mathematics, network system theory, and multi-objective comprehensive evaluation methods, have provided a mathematical foundation for the identification of bridge structural damages.[9]

In recent years, a growing number of researchers have been using the deep learning method to identify image objects. By studying the image through CNN and automatically extracting the object features from the image, the deep learning framework can show high learning ability, identification speed, and accuracy. There are two types of object detection algorithm based on deep learning, namely, the regional CNN (R-CNN) series and the methods that convert detection into regression problem solving. The former includes R-CNN,[10] Faster R-CNN,[11] and region-based fully convolutional network (R-FCN),[12] all of which have high detection accuracy but low detection speed. The latter includes You Only Look Once[13] and a single-shot multibox detector,[14] both of which have low detection accuracy but high detection speed. Since the detection of the structural problems of bridges requires a higher identification accuracy than real-time performance, in this study, Faster R-CNN was used to perform the automatic detection of the structural problems of bridges. As an engineering application of object detection, the detection of the structural problems of bridges has an important application value. In this paper, a detection model combined with soft-nonmaximum suppression (Soft-NMS) based on Faster R-CNN, which eliminates the impacts of object size and morphological properties and overcomes the shortcomings of a very large negative sample space during training, is put forward. In this study, a cascade network model of primary screening for multicategory problems and the accurate identification of single-category problems, which considerably reduces the missed detection rate and improves the detection accuracy, was also built. In addition, the identification model used in this study, with good identification effect and high practicability, can target many types of structural problem of bridges and meet the requirements of practical engineering applications.[15]

2. Methods

2.1 Soft-NMS

The NMS algorithm plays a crucial role in the Faster R-CNN algorithm by eliminating overlapping redundant frames of the same object. It achieves this by forcibly resetting the scores of adjacent detection frames to zero. Figure 1 shows a situation where the current detection results in a red frame and a blue frame, with scores of 0.8 and 0.95, respectively. As per NMS algorithm's Eq. (4), the scores are compared and reset. Consequently, the blue frame, having the highest score, is selected, whereas the red frame is mistakenly deleted owing to excessive overlap with the blue frame. This leads to a missed detection scenario. Additionally, determining the threshold and finding the optimal value for the NMS algorithm can be challenging. This often requires extensive experimentation to minimize both missed detection and false detection, making the parameter adjustment process highly complex.

In this study, the Soft-NMS algorithm was used to replace the original NMS algorithm. Equation (1) is the score reset formula of the NMS algorithm, and Eq. (2) is that of the Soft-NMS algorithm. Moreover, an attenuation function was set in the Soft-NMS algorithm on the basis of the size of the overlapping part of adjacent detection frames, instead of completely setting the score of adjacent detection frames to zero. In other words, the detection frame with a large overlap with the maximum detection frame is assigned a very low score. However, for the detection frame with only a small overlap with the maximum detection frame, its original detection score is not significantly changed.

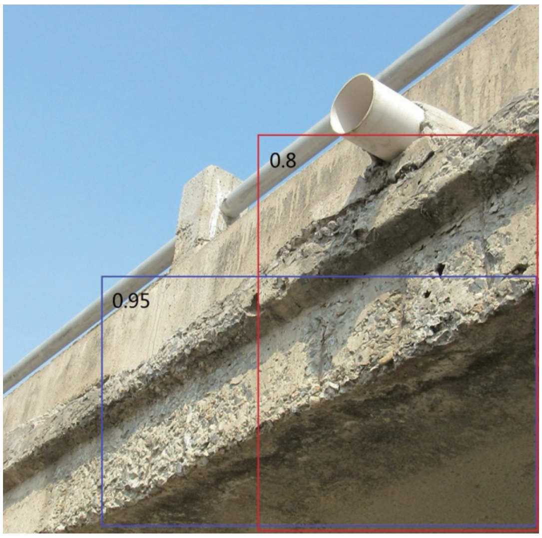


Fig. 1. (Color online) Example of NMS.

$$s_i = \begin{cases} s_i, & iou(M, b_i) < N_t \\ 0, & iou(M, b_i) \geq N_t \end{cases} \tag{1}$$

$$s_i = \begin{cases} s_i, & iou(M, b_i) < N_t \\ s_i\left(1 - iou(M, b_i)\right). & iou(M, b_i) \geq N_t \end{cases} \tag{2}$$

2.2 Automatic detection system for structural problems of bridges

Considering that the accuracy of the identification model for multicategory problems cannot meet the requirements of the accuracy of identification under the limitation of a certain confidence, an automatic detection system for structural problems of bridges with primary screening and an identification model cascade was established; it includes a primary screening network for multiple problems and a detection network cascade for a single problem. The system structure diagram is shown in Fig. 2.

3. Training and Analysis of Models

In this study, the mainstream deep learning framework, Caffe, was used as an experimental platform, and the transfer learning strategy was selected owing to the small number of datasets. In addition, the training network in this study was initialized by the pretrained model in the

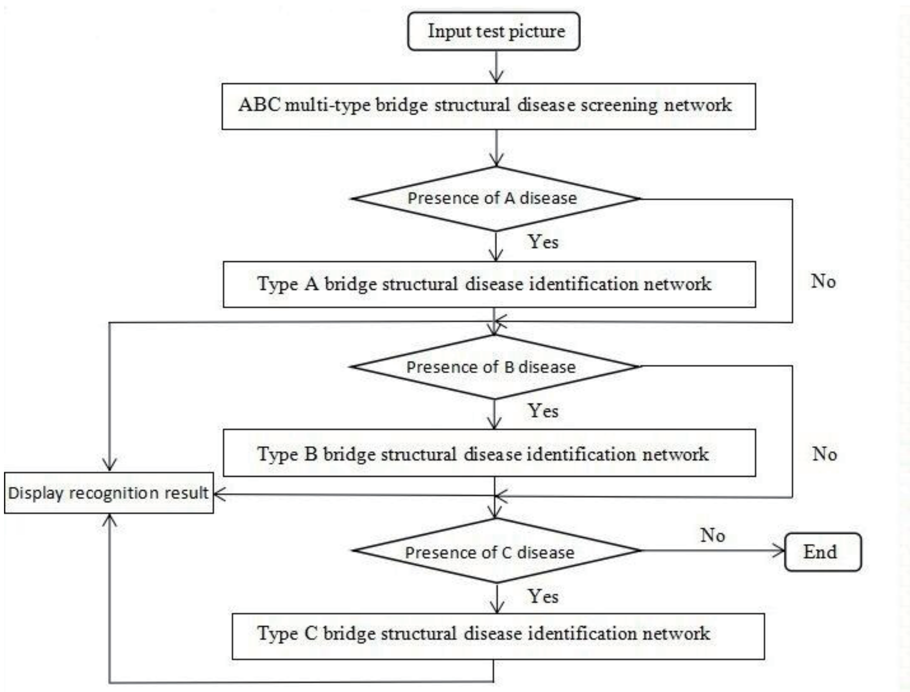


Fig. 2. Flow chart of cascade identification system.

ImageNet classification task, whereas the convolutional layer weight of the feature extraction network was initialized by the pretrained VGG16 CNN in the ImageNet classification task. Furthermore, Faster R-CNN was subjected to the end-to-end approximate joint training using the gradient descent method, and the model training was calculated with the GPU because of the large computational effort.

3.1 Selection of dataset

The image datasets in this study were obtained from photographs of the structural problems of bridges taken during manual inspection over the years and mainly include voids and pits, cracks, and white precipitate, as shown in Fig. 3. In the case of insufficient quantity, the image processing method for expansion was used to improve the generalization ability of the model. In this study, the horizontal mirror flip was used to expand the dataset, which doubled the number of datasets, and 424 voids and pits (marked as fwmm), 238 cracks (marked as lf), and 630 white precipitate (marked as bx) were obtained. Eighty percent of the dataset was used as the training set, while the remaining 20% was used as the test set. The dataset used in this study comprised the image data collected during engineering practice and was not ideal. Therefore, compared with the existing research results, the model obtained through training has a high engineering application value.

The Faster R-CNN algorithm can process images of any size, but the image sizes of problems such as voids and pits are very large, increasing the computational burden of the graphics card. The VGG16 used in this study for transfer learning was obtained from the training on the image dataset with a size of 500 × 300, and using oversized data may produce adverse effects. Therefore, in this study, the original images with sizes of 2994 × 2134 and 4608 × 3456 were converted to 600 × 450 by image processing, and a group of comparative experiments were conducted on the dataset of problems such as voids and pits. The results are shown in Table 1.

Table 1 shows that the small image dataset has greater advantages in training time and testing time, and the AP is about 3.5% higher than the training result of the original large image dataset. The convolution results of the middle layer are shown in Fig. 4 after visualization, showing that

(a) (b) (c)

Fig. 3. (Color online) Examples of structural problems of bridges. (a) Honeycomb pitted surface, (b) crack, and (c) white analysis.

Table 1
Results of comparative experiment of image size.

Image size of dataset	Training speed (s/iter)	Training time	AP	Test speed (/img)
Original image	0.449	74 min 56.839 s	AP for fwmm = 0.7203	0.145
600 × 450	0.416	69 min 26.857 s	AP for fwmm = 0.7755	0.091

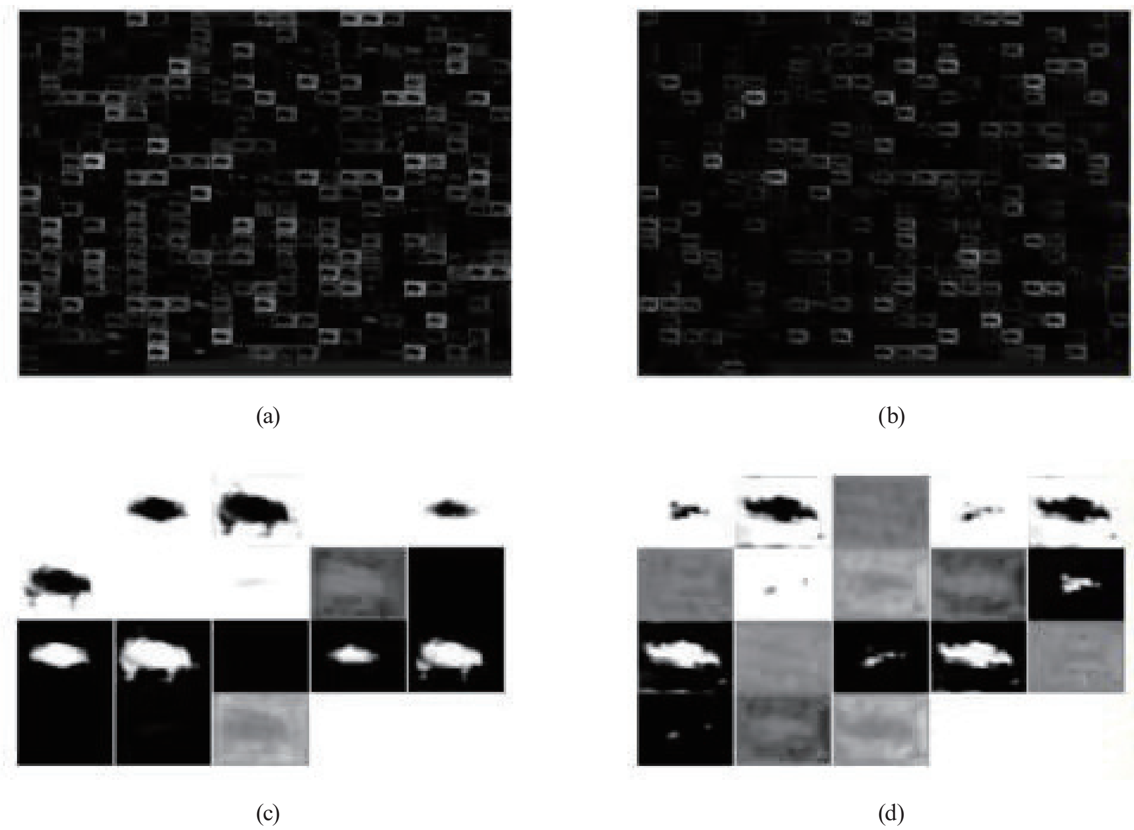
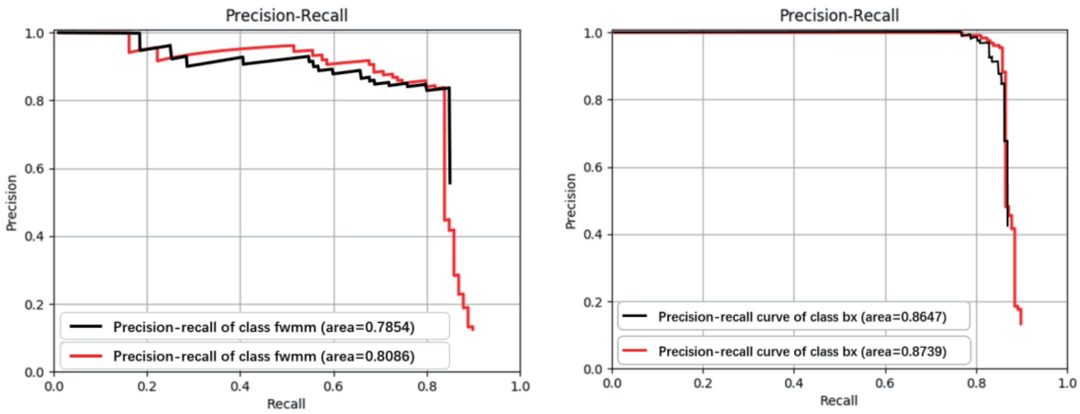


Fig. 4. Visualization of convolutional results of the middle layer in various sizes. (a) 600 × 450--rpnoutput layer, (b) master drawing--rpnoutput layer, (c) 600 × 450--rpn_cls_prob_reshape layer, and (d) master drawing--rpn_cls_prob_reshape layer.

the convolution results of the small image dataset are clearer and with better effect. Therefore, small image datasets were used in the experiments described later in this paper.

3.2 NMS replaced by Soft-NMS

Taking the problem of voids and pits as an example in this study, the comparative experiment of NMS and Soft-NMS algorithms was conducted, and the results of the *P*–*R* precision vs recall (*P*–*R*) curve of the model under the two algorithms are as shown in Fig. 5. The AP of the original Faster R-CNN algorithm using NMS is 78.54%, which becomes 80.86% after changing to Soft-NMS, which shows an increase of about 2.32%. In addition, the recall (also known as recall ratio) of the model has also been considerably improved, thereby markedly reducing the missed



(a) (b)

Fig. 5. (Color online) *P*–*R* curve under NMS and Soft-NMS. (a) *P*–*R* curve of fwmm model in NMS and Soft-NMS and (b) *P*–*R* curve of box model in NMS and Soft-NMS.

detection rate, which is more in line with the original intention of detecting structural problems of bridges. The APs of identification models of white precipitate before and after the improvement are 86.47 and 87.39%, respectively, which shows an increase of about 1%. On the other hand, there is less overlap of the crack problem, so the improvement is unclear.

3.3 Cascade network model

According to the system structure diagram in Fig. 2, the best primary screening network model for multiple bridge structural problems needs to be trained first, and the identification accuracies of the three types of bridge structural problem are 63.54, 62.57, and 61.17%, respectively. Figure 6 shows the *P*–*R* curve. In the automatic monitoring system for structural problems of bridges, the confidence rate of the network model was reduced to decrease the missed detection rate and improve the recall rate. The APs of detection models of single problems, namely, voids and pits, cracks, and white precipitate, are 80.86, 81.42, and 87.39%, respectively, and the *P*–*R* curves of three secondary models are each shown in Fig. 7. Moreover, the accuracy and the identification effect of a single problem are much better in the secondary model than in the primary model.

The main objective for the primary screening network model is to reduce the missed detection rate, so that the images with suspected problem types can be transferred to the next level for further accurate identification in the detection model for a single problem. Therefore, the confidence thresholds of the primary screening network should be discussed first. If the model identifies that the confidence of the detection frame is greater than ω, the problem in the detection frame should be considered as the target of correct detection, and the image should be input into the single-problem detection model, which corresponds to the next level. However, if the confidence is less than ω, it should be assumed that no target is detected in the detection box. The missed detection rates of three types of problem target obtained through experiments under different confidence thresholds are shown in Table 2. When the confidence rate of the primary

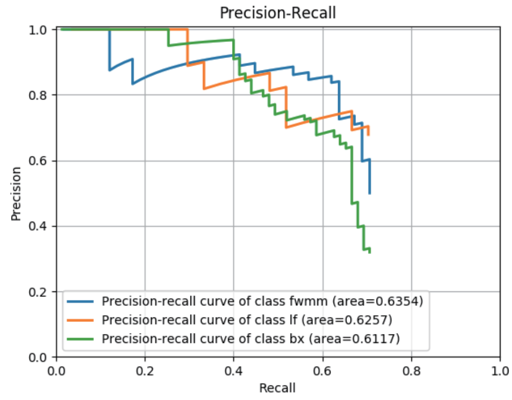


Fig. 6. (Color online) *P–R* curve of primary screening network.

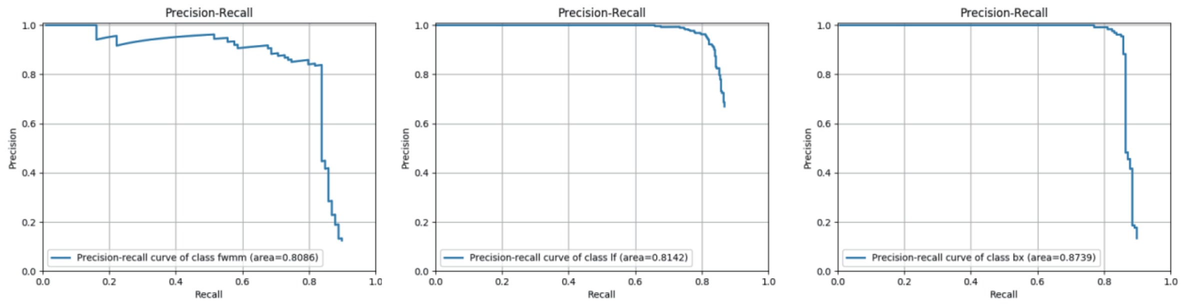


Fig. 7. (Color online) *P–R* curves of secondary identification network. (a) *P–R* curve of honeycomb pitted surface, (b) fracture model *P–R* curve, and (c) white analysis model *P–R* curve.

Table 2
Missed detection rates of three types of problem target under different confidence thresholds.

Confidence threshold	Fwmm missed detection rate (%)	lf missed detection rate (%)	Bx missed detection rate (%)
0.1	4.06	1.86	3.91
0.2	8.94	5.59	7.81
0.3	13.01	8.07	10.94
0.4	13.82	8.70	12.50
0.5	13.82	9.94	16.40
0.6	15.45	11.80	19.53
0.7	17.07	13.66	23.44

screening network model is 0.1, the missed detection rate is the lowest. Therefore, 0.1 was used as the confidence threshold of the primary screening network in this study.

3.5 Parameter settings

In this study, the end-to-end training method of Faster R-CNN was adopted, and the parameter settings of the four subnetworks in the cascaded network model were determined after optimization and algorithm improvement, as shown in Table 3.

Table 3
Parameter settings.

Model	No. of iterations (n)	Anchor		Learning rate	
		Size	Length–width ratio	Front n/2	Rear n/2
Primary Screening	10000	642, 1282, 2562, 5122, 10242	1:8, 8:1, 1:7, 7:1, 1:6, 6:1, 1:5, 5:1, 1:4, 4:1, 1:3, 3:1, 1:2, 2:1, 1:1	0.002	0.001
Secondary Fwmm	10000			0.0018	0.0009
Secondary bx	12000			0.0008	0.0004
Secondary lf	8000	3202, 4802, 6402, 10242, 12002		0.0024	0.0012

4. Conclusions

In this study, we built upon the Faster R-CNN algorithm by incorporating the Soft-NMS algorithm to enhance the original NMS algorithm. Furthermore, the training model was optimized, and identification models were combined to create an automatic detection system for structural problems of bridges. However, the dataset used in this study consisted solely of manually captured image data from daily inspections, resulting in significant variations in angles, scenes, and conditions. As such, this dataset may not be ideal. Nevertheless, the developed model holds great application value and can be directly implemented in bridge detection projects.

To fully leverage the benefits of deep learning, it is crucial to address the limitations of insufficient and incomplete datasets in this study. Future research should focus on expanding the dataset to achieve more robust and accurate results. Additionally, it is recommended to develop a corresponding user interface to display the identification results or create detection software specifically designed for identifying the structural problems of bridges. These advancements will enhance the practicality and usability of the proposed method.

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