A semantic segmentation method for exposed rebar on dam concrete based on Unet

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Abstract: Exposed rebar is an essential factor affecting the safety of the dam. In the past, manual inspection is a significant way to monitor exposed rebar risk. However, it is time-consuming, inefficient and difficult to quantitative evaluate, such as the exposed rebar area. A semantic segmentation method based on the Unet is proposed to replace the manual inspection for the dam exposed rebar automatic detection. Thirty-eight high-resolution images of dam exposed rebar are collected. Unet and the VGG16 backbone are adopted. The results indicated that Unet's mIoU on the test set reaches 0.94, which proves to be an efficient way to detect the dam exposed rebar.

1. Introduction

Reinforced concrete is widely used in civil engineering because of its advantages such as low cost, durability and wide material sources [1]. Steel corrosion in concrete has become a significant concern in the world and is considered to be the primary reason affecting the durability of concrete structures [2-4]. Dam concrete belongs to the mass reinforced concrete. The construction quality is more or less poor during the construction period, which makes the primary reinforcement, auxiliary reinforcement or stirrup of concrete being exposed on the dam surface. The exposed rebar will lead to the corrosion phenomenon, and the cross-section of the rebar will become smaller after a long time of corrosion, leading to the decline of the mechanical properties of the dam. Therefore, the safety service life of the structure is reduced.

Manual inspection on dam exposed rebar is commonly used at present. However, it has problems such as time-consuming, difficulty in global coverage and low efficiency.

In recent years, the deep learning technique represented by the fully convolutional networks (FCN) [5] is continuously surpassing the previous image semantic segmentation techniques in the pixel level classification task. It is gradually applied in various fields.

In this paper, on-site exposed rebar image data of a concrete dam is collected. An exposed rebar data set is established, and then is identified by using the Unet technology based on FCN, thus providing an effective way to automatic detection and liberate human resources.

2. Unet model

UNet [6] are semantic segmentation deep learning models developed from FCN model. As shown in Figure 1, Unet uses skip connection to connect the features in the same scale. In this way, more low-
level features are integrated in the recovered features. Features of different scales are fused, so that multi-scale prediction can be carried out. The four times upsampling also makes the segmentation image's edge and other information more refined. In particular, Unet adopts a method of splicing to fuse the features together in channel dimension and finally form thicker features, which is very different from other common segmentation networks. In this study, we use the same convolutional mode which means that the convolved feature image size is the same as the input image size because we found that there is not much effect on the recognition results.

![Figure 1. Architecture of Unet, in which the backbone is VGG16.](image)

**3. The model flow chart**

The flowchart of our semantic segmentation method is shown in Figure 2 and demonstrated as follows:

- S1: Obtain images from the concrete surface of the dam, and label the images with or without exposed rebar pixel by pixel;
- S2: The defect image and its labelled image are processed by sliding window, and image enhancement processing should be carried out for defect images;
- S3: The generated local images are divided into the training set and test set, which are used for model training and test;
- S4: Train the Unet according to the training set in step S3;
- S5: The model trained according to step S4 is used to classify the images pixel by pixel in the test set from step S3.

![Figure 2. Flowchart of our semantic segmentation method](image)
4. Examples

The image data is derived from the surface exposed rebar image of an arch dam, which is obtained by taking photos with a mobile phone camera. The resolution of the surface exposed rebar image is 3456*4608, and a total of 36 on-site images are collected. The local exposed rebar images were intercepted at the resolution of 572*572. The stride of the sliding window was 286, and each exposed rebar image was enhanced by rotating the angle to 90, 180, and 270 degrees, and a total of 1589 images were finally generated. According to the ratio of 4:1, the local images were divided into the training set, and test set, respectively. The Unet and the VGG16 backbone are adopted. The deep learning library TensorFlow is used for model training.

The cross-entropy loss function is used as follows:

\[
\text{Loss} = -y \log y' - (1 - y) \log (1 - y')
\]

where, \(y\) denotes the positive and negative label; \(y'\) denotes the output probability.

The evaluation indexes of the model are as follows:

\[
\text{mIoU} = \frac{1}{M} \sum_{m=1}^{M} \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}}
\]

where, \(M\) denotes the patches number which is computable. \(\text{TP}\) denotes the true positive predictions; \(\text{FP}\) means the false positive predictions; \(\text{FN}\) denotes the false negative predictions.

The model training process is as follows:

![Graphs showing loss and mIoU over epochs for training and testing sets.](image-url)

**Figure 3.** The training process of Unet
For the Unet, the initial learning rates are set as 0.001, and the SGD updater is used. The weight decay to use for regularizing the model is set $10^{-5}$ to prevent overfitting. The Unet are trained for 1000 epochs, and the batch size is set as 10.

As can be seen from Figure 3, the Loss and mIoU converge after about 400 epochs on both the training and test sets. However, there are some unstable jump points in the training process. The mIoU finally achieve 0.94 on the test set. Meanwhile, Figure 4 shows some semantic segmentation results on the test set. The results show that the Unet can distinguish the difference between the rebar and the paint with the same colour, which indicates that the Unet is an efficient way to detect the exposed rebar of the dam.

5. Conclusion
This study adopts a segmentation method for dam exposed rebar detection. The Unet is developed from classic FCN and can achieve pixel-level prediction. The details through the pixel-level information such as the area of exposed rebar can be acquired automatically, which is very suitable for exposed rebar detection. The on-site dam exposed rebar images are used to verify the Unet, which is finally proved to be useful. In the future, more data should be used to improve the exposed rebar detection effectiveness.

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