Automatic detection for calcium leaching of dam concrete based on DeepLabv3+

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Abstract: Long-termly resistance to upstream water, dam concrete is prone to calcium leaching. It will lead to lesions of the concrete and gradual attenuation of strength, impermeability and frost resistance, thus reducing the durability and service life of the structure and even threatening the safe operation of the dam. At present, the concrete leached calcium is mainly checked by the workforce, but it is time-consuming, inefficient, and hard to quantitatively evaluate, such as the area of leached calcium. A semantic segmentation method based on the DeepLabv3+ with ResNet50v2 backbone is proposed to identify the calcium leaching of dam concrete automatically. The calcium-leached concrete data set is established, including 94 high-resolution images in dam corridors to verify the method. The results indicated that the DeepLabv3+ model finally reaches 0.72 mIoU on the test set, which is a practical way to detect calcium leaching of dam concrete.

1. Introduction

Deterioration of concrete structures subjected to aggressive water is often characterized by the leaching of calcium from hydrates [1]. The action of calcium leaching is an important durability problem for the cement-based materials served in long-termly in the environmental water [2]. Calcium leaching of dam concrete is conventional and often regarded as a normal phenomenon. Ca(OH)2 is the main hydration product of ordinary Portland cement. It can produce white sediments in the concrete dam tunnel wall, the outlet of the drainage hole and collecting ditch, etc. Meanwhile, Ca(OH)2 in concrete is a crucial component to maintain the stability, strength and impermeability of cement hydration products. Besides, it will lead to leakage around the dam dissolved bedrock if the calcium precipitations of dam foundation backfill concrete are more enough. The leached calcium in the curtain will increase the water leakage, which can increase the dam foundation pressure. It will also make the drainage hole failure if the calcium precipitations obstruct the hole. Furthermore, for the reinforced concrete, the loss of calcium will make the steel more susceptible to corrosion. All these will affect the stability and safety of the dam [3-4], so the calcium leaching of dam concrete cannot be ignored.

Manual inspection is a commonly used monitoring method for calcium leaching of dam concrete at present. However, there are some problems such as time-consuming, difficulty in comprehensive 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 image pixel-level classification task. It is gradually being applied in various industries.

In this paper, on-site calcium-leached concrete image data from a concrete dam is collected. A calcium-leached concrete data set is established, and then is identified by using the DeepLabv3+ technology based on FCN, thus providing an effective way to liberate human resources.

2. DeepLabv3+
DeepLab series [6-9] are semantic segmentation deep learning models developed from FCN model. There are two technical hurdles in the application of basic FCN model: downsampling, and spatial invariance. The downsampling method will reduce the resolution, especially at the high-level layers. The spatial invariance means that obtaining object-centric decisions from a classifier requires invariance to spatial transformations, inherently limiting the spatial accuracy. DeepLabv1 employs the atrous convolution algorithm and conditional random field (CRF) to address the down-sampling and the spatial invariance, respectively. DeepLabv2 uses atrous spatial pyramid pooling (ASPP) to robustly segment objects at multiple scales. To encode multi-scale information, DeepLabv3 proposes a cascaded module and an improved ASPP module. The cascaded module gradually doubles the atrous rates and the improved ASPP module augmented with image-level features probes the features with filters at multiple sampling rates and effective field-of-views. DeepLabv3+ extends DeepLabv3 by adding a simple yet effective decoder module to refine the segmentation results, especially along object boundaries. For backbone, DeepLabv1 is constructed by VGG-16. DeepLabv2 and DeepLabv3 use the ResNet. DeepLabv3+ (see Figure 1) adopts the ResNet and Xception.

3. ResNetv2
The ResNet backbone [10-11] is put forward to solve the problem that deeper networks are more challenging to train. This kind of network is equivalent to add a new channel of the input so that the input can reach the output directly. Then, the optimization objective changes from the original output H(x) to the residual between the H(x) and input x. The ResNet backbone shows excellent characteristics in precision and convergence by using an extremely deep network. The ResNet series have two versions named ResNetv1 and ResNetv2 (Figure 2). ResNetv2 adopts the identity after-addition activation to make information propagation smoother. The asymmetric after-addition activation is equivalent to constructing a pre-activation residual unit. In this paper, the ResNetv2 model is adopted to replace the ResNetv1 backbone from DeepLabv3+.

Figure 1. Architecture of DeepLabv3+
Figure 2. ResNetv1 and ResNetv2 units. The units consist of the same components, while the orders are different.

4. The model flow chart
The flowchart of our semantic segmentation method is shown in Figure 3 and demonstrated as follows:

S1: Obtain images from the concrete surface of the dam, and label the images with or without calcium-leached concrete pixel by pixel;
S2: The image and its labelled image are processed by size scaling;
S3: The generated scaled images are divided into a training set and test set, which are used for model training and test;
S4: Train the DeepLabv3+ 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 3. Flowchart of our semantic segmentation method

5. Examples
The image data is derived from the calcium-leached concrete of a dam, which is obtained by taking photos with a mobile phone camera. The resolution of the image of calcium-leached concrete is 4032*3024, and a total of 94 on-site images in dam corridors are collected. The images are scaled to 513*513. According to the ratio of 4:1, the scaled images were divided into the training set and test set, respectively. The deep learning library Tensorflow is used for model training and prediction.

The cross-entropy loss function is used as follows:

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

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

The evaluation indexes of the model are as follows:
\[
mIoU = \frac{1}{M} \sum_{m=1}^{M} \frac{TP}{TP + FP + FN}
\]  
(2)

where, M denotes the images' number. TP denotes the true positive predictions; FP means false positive predictions; FN denotes the false-negative predictions.

The model training process is as follows:

![Figure 4. The training process of Deeplabv3+](image-url)
For the Deeplabv3+, the initial learning rates are set as 0.001, and the Adam updater is used. The weight decay to use for regularizing the model is set $10^{-5}$ to prevent overfitting. The Batch Normalization (BN) parameter is set $\epsilon=10^{-6}$, which is a small constant to prevent division by zero when normalizing activations by their variance in BN. The Deeplabv3+ are trained for 2000 epochs, and the batch size is set as 3.

As can be seen from Figure 4, the Loss and mIoU converge after about 250 epochs on both the training and test sets except the training Loss, which decreases gradually. However, there are some unstable jump points in the training process. The mIoU can achieve 0.72 on the test set. Meanwhile, Figure 5 shows some of the semantic segmentation results on the test set. The results show that the Deeplabv3+ can distinguish the difference between the pipe and the calcium-leached concrete with the same colour, which indicates that the Deeplabv3+ is a powerful method to detect the calcium-leached concrete of the dam.

6. Conclusion
This study adopts a segmentation method for calcium-leached concrete detection. The Deeplabv3+ is developed from the classic FCN and can achieve pixel-level prediction. The details can be acquired automatically through the pixel-level information such as the area of calcium-leached concrete, which is very suitable for leached calcium concrete estimation. The on-site dam calcium-leached concrete images are used to verify the Deeplabv3+, which is finally proved to be useful.

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