A Semantic Segmentation Method for Dam Leakage Detection Based on FCN

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Abstract: Leakage is an important factor affecting the safety of the dam. In the past, manual inspection is a significant way to monitor leakage risk. However, it is time-consuming, inefficient and difficult to quantitative evaluate such as the leakage area. A semantic segmentation method based on the fully convolutional network is proposed to replace the manual inspection for the dam leakage automatic detection. Thirty-eight high-resolution images of dam leakage are collected. FCN-8s and VGG16 backbone are adopted. The results indicated that the FCN-8s achieves the mIoU to 0.59 on the test set, which proves to be an efficient way to detect the dam leakage.

1. Introduction

Dam leakage not only affects the performance of power generation, water supply, irrigation, and other projects but even directly threatens the project’s flood control safety, causing dam break risk. The leakage of the dam can be divided into dam body leakage, leakage at the contact of the dam body and surrounding rock mass, and leakage of surrounding rock mass. Different types of leakage produce some extent damage to different dam types [1-4]. For the earth-rock dam, leakage will destroy the anti-seepage and drainage facilities, lead to dam foundation and structure failure, and reduce dam slope stability. For the concrete dam, the uplift pressure will reduce the stability of the dam body. The groundwater on both sides will affect the security of the dam foundation and surrounding rock. The leakage will also lead to hydro-chemical damage to the dam foundation and structure.

Leakage monitoring and manual inspection are commonly used monitoring methods for dam leakage at present. However, leakage monitoring, a point-type distribution method, is difficult to carry out comprehensive coverage of the dam. Therefore, manual inspection is still an indispensable monitoring method, but 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 many professions.

In this paper, on-site leakage image data of a concrete dam is collected, a data set is first established. Then, the leakage data set of the dam is identified by using the technology based on FCN, thus providing an effective way to liberate the workforce.
2. FCN model

Different from the classic CNN [6] in convolution with a full connection layer to get a fixed-length feature vector for classification, FCN can accept any size of the input image. The deconvolution layers are applied to upsampling the feature map of the final convolution layer and make the feature map back to the same size of the input image. Thus, the network can have a prediction on each pixel, while retaining the original input space information of images. Figure 1 is the architecture of FCN adopted in this paper. Its main ideas include:

1. Adopting the end-to-end structure, which makes the network easy to train;
2. Cancel the full connection layer;
3. When the feature map of the image is down-sampling to a certain extent, reverse up-sampling is performed to match the semantic segmentation annotation map of the image;
4. Up-sampling will lose some information. Therefore, FCN takes into account the response of the shallow layer in the network to better predict the details in the image. As shown in Figure 2, Pool4 and Pool3 responses were considered as outputs of model FCN-16s and FCN-8s, respectively, and combined with the original output of FCN-32s for the final semantic segmentation prediction.

Figure 1. Architecture of FCN-8s, in which the backbone is VGG16.

Figure 2. Skip Layer of FCN[5]

3. 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 defects pixel by pixel;
S2: The defect image and its labelled image are processed by sliding window or size scaling, 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 FCN 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

4. Examples

The image data is derived from the surface leakage image of an arch dam, which is obtained by taking photos with a mobile phone camera. The resolution of the surface leakage image is 3456*4608, and a total of 38 on-site photos are collected. The image data was first scaled to 960*960, and then the local leakage images were intercepted at the resolution of 480*480. The stride of the sliding window was 240, and each leakage image was enhanced by vertically flipping, and a total of 540 images were finally generated. According to the ratio of 4:1, the local images were divided into a training set and test set, respectively. The FCN-8s and the backbone VGG16 are adopted. The deep learning library TensorFlow is used for model training.

The cross-entropy loss function is used as follows:

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

(1)

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

The evaluation indexes of the model are as follows:

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

(2)

where, \( M \) denotes the patches number, which is computable. \( TP \) 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 FCN-8s

(a) Loss

(b) mIoU
(a) Original image                                (b) Labelled image                  (c) FCN-8s recognition result

Figure 5. FCN-8s for leakage image semantic segmentation

For the FCN-8s, 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 10e−5 to prevent overfitting. The FCN-8s are trained for 1000 epochs, and the batch size is set as 15.

As can be seen from Figure 4, the Loss and mIoU converge after about 200 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 finally achieve 0.59 on the test set. Meanwhile, Figure 5 shows some semantic segmentation results on the test set, which indicates that the FCN-8s is an efficient way to detect the leakage of the dam.

5. Conclusion
This study adopts a segmentation method for dam leakage detection. The FCN is developed from classic CNN and can achieve pixel-level prediction. The details through the pixel-level information, such as the leakage area, can be automatically acquired, which is very suitable for leakage detection. The on-site
dam leakage images are used to verify the FCN-8s, which is finally proved to be useful. In the future, higher performance models and more data should be used to improve the leakage detection effectiveness.

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