Deep Learning with Spatial Constraint for Tunnel Crack Detection

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ABSTRACT

Cracks are the most common defect on the surface of tunnels, which potentially brings threaten to the safety of the tunnel and the running vehicles. Timely repairing of the crack is of critical importance. In the past two decades, various vehicle platforms have been developed on the purpose of efficient crack detection and maintenance. With these platforms, images can be captured in a traffic speed, and automatic methods can be developed for fast crack localization. However, for image-based crack detection, traditional methods often meet difficulties in handling cracks with low contrast and poor continuity. In this paper, deep learning based techniques are exploited for feature learning and representation for crack detection. A novel deep neural network is presented for pixel-level crack recognition. Hierarchical features in different stages of the convolution are fused together to overcome the influence of noise and a spatial constraint placed on the target pixels is used to guarantee the crack continuity. In the experiment, a tunnel crack dataset is constructed for performance evaluation. Experimental results demonstrate the effectiveness of proposed method.

INTRODUCTION

Tunnels are commonly constructed as a part of the highway especially in mountain regions. For example in China, the highway tunnel of Qinling Zhongnan Mountain in Shaanxi province has a length of 18.02 Km, the highway tunnel of Maiji Mountain in Gansu province has a length of 12.29 Km and the highway tunnel of West Mountain in Shanxi province has a length of 13.65 Km, as shown in Figure 1. Once the tunnels are set into operation, defects and damages will appear after a long time of use. For example, the uneven force outside the tunnel may deform the tunnel lining, and make cracks on the tunnel surface. These cracks may lead to water leaking, and consequently the freezing damage in cold winter. Meanwhile, a crack looks like a minor

Figure 1. Typical long tunnels in China

Figure 2. Traditional testing and repairing method

defect, but it can easily deteriorate into more serious damage such as a wide cleft. In such situation, the lining board would fall down and threat the safety of high-speed vehicles running in the tunnel. Thus, it is necessary to fix a crack as early as possible. Traditionally, the defects including the cracks are visually inspected by testers by closing the tunnel, and then repaired by professional workers, as illustrated by Fig. 2. This procedure is time-wasting and labor intensive.

Due to the requirement of timely mending of cracks, fast crack detection techniques have been developed in the past two decades. A tunnel lining inspection system named Tunnelings was developed by Spanish Euroconsult and Pavemetrics Company, as shown in Fig. 3 (left), which used cameras and laser sensors to scan the tunnel lining with a 1mm resolution at a speed up to 30 km/h (Gavilán *et al.*(2013)). The platform that carries the laser cameras was installed on a truck capable of running on rails and on flat terrain. Another tunnel inspection system named tCrack was developed by Swiss Terra Company, as shown in Fig. 3 (middle), which includes ten CCD cameras, mounted on a site vehicle, can recognize cracks of more than 0.3 mm in width, and can run at a speed of 2.5 km/h. A third equipment named MIMM-R was developed by Japanese Keisokukensa Company, which integrated CCD cameras, laser scanner and Ground Penetrating Radar for inspecting cracks, leakage, tunnel deformation and tunnel lining cavities (Huang *et al*. (2017)). It can detect cracks at a precision of 0.2mm and at a speed of 70 km/h.

For tunnel crack detection, image-based methods have been widely used. Generally, cracks are darker than those of their surroundings in image, resulting in different gray scale values compared to the background (Zou *et al.*(2012), Kaul *et al.*(2012), Oliveira *et al.*(2013), Amhaz *et al.*(2016), Koch *et al.*(2015)). This property allows threshold segmentation techniques as a first step to segment the image and extract potential crack feature (Li *et al.* (2011)). Roli (1996) proposed a method utilizing conditional texture anisotropy for crack detection. Qu *et al.* (2016) detected the tunnel lining cracks by firstly eliminating the seams on the concrete surface.

Figure 3. Three representative tunnel inspecting systems: Tunnelings, tCrack and MIMM-R.

Fujita *et al.*(2006) proposed two preprocessing methods using the subtraction method and the Hessian matrix. Since the local window is fixed, these methods cannot be flexibly applied to different widths. However, these methods only use low-level features for crack detection, and may suffer to failure when the cracks have low contract to the background or bad continuity.

In the past several year, deep convolutional neural networks (DCNN) have achieved success in many computer vision applications such as object detection, image segmentation, and image retrieval, etc. Features abstracted by DCNNs are found to be able to represent the target in an image in a high level, which can be effectively used for high-level visual perception and reasoning. Deep convolutional features were also found to be useful for crack detection (Zhang *et al.*(2016), Schmugge *et al.*(2017)). In this paper, we proposed a robust crack detection method by fusing hierarchical deep convolutional features to represent the cracks. Meanwhile, to overcome the problem that line structures are not well modeled in the traditional deep models, we present a spatial constraint in training our deep model. With this spatial constraint, the detection output will be a continuous line structure, although the cracks in the original image have low continuity.

THE PROPOSED METHOD

The model detects cracks via pixel-wise semantic segmentation and enhances the crack continuity by predicted positive links.

Network Architecture

We build a fast crack segmentation architecture inspired by the Unet network (Ronneberger *et al.* (2015)), a fully convolutional network. Unet is a deep convolutional encoder-decoder architecture designed for pixel-wise semantic segmentation, which contains an encoder network and a corresponding decoder network. As shown in Fig. 4, it consists of a down-sampling encoder part and an up-sampling decoder part.

For image-based crack detection, a larger receptive field obtained by down-sampling convolution feature is useful to overcome the influence of noise, and the decoder part can refine crack edges

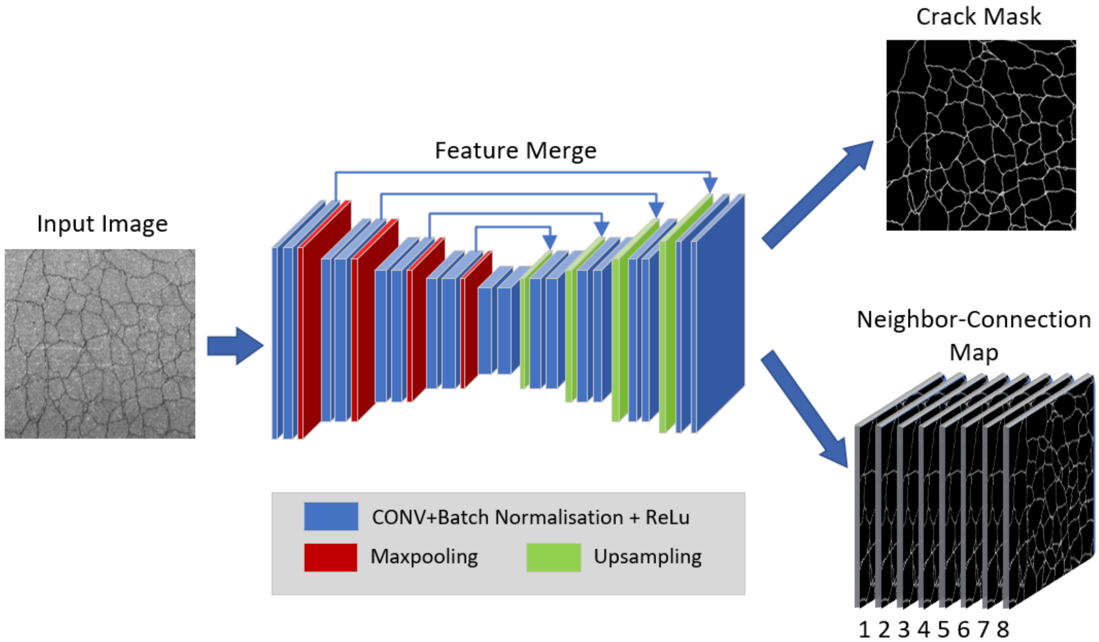

Figure 4. Network Structure

with higher precision by using the encoded features. The encoder network is similar to the convolutional layers in the VGG network (Simonyan *et al.*(2015)), but is constructed with less convolution channels. It consists of the repeated application of two 3×3 convolutions. Each of them is followed by a rectified linear unit (ReLU) and a 2×2 max-pooling operation with a stride of 2 for down-sampling. Different from VGG network, we double the number of feature channels before the down-sampling step such that the loss of feature information can be reduced. In the decoder part, we use nearest neighbor up-sampling to increase the size of feature and merge corresponding encoder layer features using point multiplication to reduce the amount of parameters. At the final layer, a 1×1 convolution is used to map each 32-component feature vector to the crack mask and the 8 neighbor-connection maps. After each convolution operation, a batch-normalization step is applied to the feature maps, except for the final convolution layer. The number of model parameters are only one-fifth of Unet. Experimental results show that this network structure is simple and effective.

Spatial Constraint

A crack is a line structure that holds good continuity in a global perspective. Since the semantic segmentation just makes independent judgments for each pixel regardless of the connectivity of other positive pixels, the detected cracks may be not continuous by missing part of the structures. In our design, a special spatial continuity constraint is used to enhance crack continuity in the training process. In fact, crack continuity can be effectively used for reasoning missing data caused by noise during data acquisition. In our work, the ground-truth cracks are labeled in single-pixel width, so the crack continuity relationship can be built by determining if the pixel is belonging to a line. In our model, we predict 8 neighbor-connection maps to solve this problem as illustrated by Fig. 5.

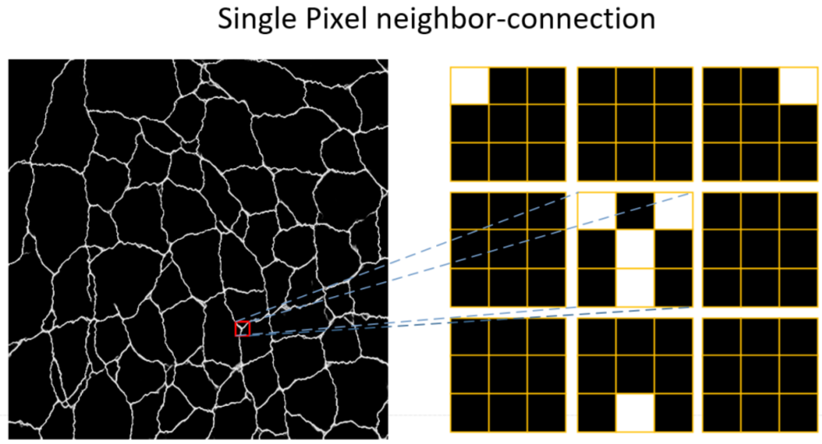

Figure 5. Neighbor-connection map

Loss Function

The training loss is a weighted sum of loss on pixels and loss on positive neighbor connections, as formulated by

$$L = L_{pixel} + \lambda L_{connected} \,. \tag{1}$$

When calculating crack loss, it is unfair to put the same weight on all positive pixels. We use classes-balance cross-entropy loss to solve this problem. We also use cross-entropy loss to calculate the neighbor-connection loss, but only positive pixels will be taken into account. The balance parameter λ is set to 5 across all the experiments.

EXPERIMENTS AND RESUTLS

Data collection. A fast tunnel inspecting system is developed by Wuhan ZOYON Company. As shown in Fig. 6, the system is equipped on a truck and composed of line-scan CCD cameras, LED light, infrared thermography and controller mount. High resolution line-scan CCD cameras capture the tunnel lining images under high-power LED illumination. Tunnel lining images are first pre-processed to compensate image shift caused by the vibration of the vehicle platform, and then mosaicked into panorama to support the detection of cracks, water leakage and other tunnel lining defects. The inspection system can identify cracks with 0.2mm width at a driving speed of 0-80 km/h. A number of 328 tunnel crack images are collected, in which 250 are used for training, and the remaining 78 are for test.

Implementation Details. It turns out that it is necessary to augment train dataset in crack detection. At first, the input images are scaled by 0.5 to 2 times and rotated at a probability of 0.5 by a random angle of 0 to $\pi/2$. Secondly, random distortion and affine transformation will be implemented on the image according to its mask. Thirdly, random cropping will be conducted with areas ranging from 0.5 to 1, and aspect ratios ranging from 0.5 to 2. Fourthly, the images are resized uniformly to 512×512. Finally, skeleton extraction algorithm is used to ensure that each crack label is a single-pixel line structure.

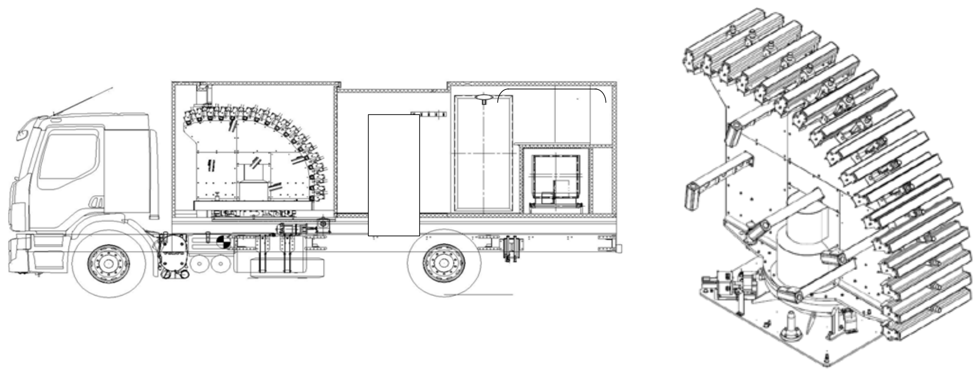

Figure 6. ZOYON tunnel inspecting system

The models are optimized by SGD with a momentum of 0.9 and a weight decay of $5\times10^{-4.}$ All convolution weights are randomly initialized by the Xavier method and the biases are set to 0. The learning rate is set to 10^{-3}. The whole algorithm is implemented using PyTorch 0.4.0. When training with a batch size of 32 on 2 GPUs (GTX 1080TI), it takes about 0.33s per iteration, and the whole training processing takes about 2 hours.

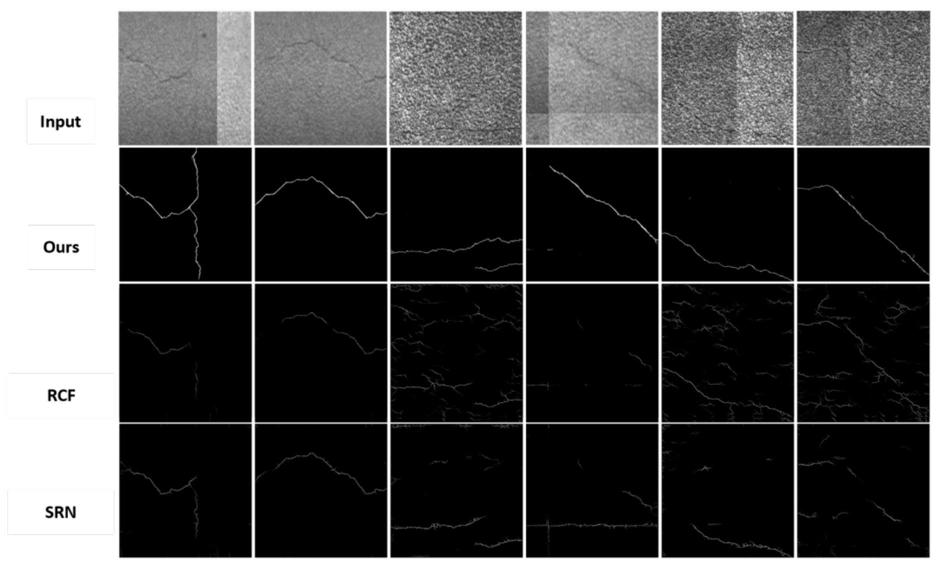

Figure 7. Results obtained by different methods on six sample images

Results. We compare the performance of ours with current state-of-the-art e deep learning based methods on six images randomly sampled from the test dataset. The results are shown in Fig.7. The results generated by RCF (Liu *et al.*(2017)) and SRN (Ke *et al.*(2017)) need to be post-processed by the standard non-maximum suppression (NMS) to thin the crack maps. The results obtained by the proposed method are directly evaluated without any post-processing procedure. Table I lists the results obtained by the proposed method and four comparison methods, which are DeepCrack (Zou *et al.*(2019)), SRN, HED (Xie *et al.*(2015)) and RCF. The proposed method obtains a highest F-Measure value of 0.9068, while the precision and recall values are also the highest among all comparison methods.

Table I: Performances of Different Methods

Method	Proposed	DeepCrack Zou, et al. (2019)	SRN Ke, et al. (2017)	HED Xie, et al. (2015)	RCF Liu, et al. (2017)
Recall	0.9224	0.8122	0.7214	0.7105	0.7349
Precision	0.8917	0.8460	0.7748	0.8587	0.7967
F-Measure	0.9068	0.8288	0.7471	0.7776	0.7646

CONCLUSION

In this paper, a novel deep learning network was proposed for crack detection from tunnel lining images. In this network, a spatial constraint was embedded by checking the continuity of cracks in eight-neighbor crack maps. A tunnel crack dataset containing 328 images was collected for performance evaluation. Experimental results demonstrated that, the proposed method extracted cracks with better continuity than other competing methods, which led to the highest values in precision, recall and f-measure among all comparison methods.

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