proceedings

MDPI

Proceedings

Development of Delamination Detection System for Concrete Decks by Using Convolutional Neural Network †

Takahiro Kashiwa [1,*], Kohei Nagai [2], Hitoshi Tatsuta [3], Helmut Prendinger [4], Kou Ibayashi [5] and Juan José Rubio Guillamón [6]

1 Faculty of Engineering, The University of Tokyo, Tokyo 153-8505, Japan
2 Institute of Industrial Science, The University of Tokyo, Tokyo 153-8505, Japan; nagai325@iis.u-tokyo.ac.jp
3 Nippon Engineering Consultants CO., LTD., Tokyo 170-0003, Japan; tatsuta@ne-con.co.jp
4 National Institute of Informatics, Tokyo 101-8430, Japan; helmut@nii.ac.jp
5 Nagaoka National College of Technology, Niigata 940-8532, Japan; ibayashi@nagaoka-ct.ac.jp
6 Barcelona School of Informatics, Universitat Politècnica de Catalunya, 08034 Barcelona, Spain; kendixd@gmail.com
* Correspondence: kashiwa@iis.u-tokyo.ac.jp; Tel.: +81-3-5452-6655

† Presented at the 18th International Conference on Experimental Mechanics, Brussels, Belgium, 1–5 July 2018.

Published: 28 May 2018

Abstract: Bridges in Japan, especially those managed by municipalities, deteriorate over time. Due to lack of civil engineers in municipalities, appropriate and automated assistance for degradation judgement is thought to be important for the concerned authorities. Automated judgement systems for some types of damage (e.g., cracks) started to be developed by geometrical approaches. Yet, there is no comprehensive method to detect more complicated types of damage, such as delamination, for regular inspection. This research aims to develop a delamination-detection system which identifies the location of the damage. Images with delaminated parts were provided by Niigata Prefecture (in Japan), and annotation of the location of delamination and/or rebar exposure was conducted. Fully Convolutional Network (FCN), one of the deep learning networks for pixel-to-pixel segmentation, was used to detect the areas of the delamination and rebar exposure. The result of the training aided by FCN showed a good agreement with the result with the naked eye. The soundness, judged based on the FCN result according to the inspection code of Niigata Prefecture, was close to the soundness judgement at the site. These outcomes support the reliability of the system to detect delamination and rebar exposure in manual inspection. This technology is expected to be used in bridges' inspection at municipalities, which have a lack of inspection engineers.

Keywords: damage detection; delamination; regular inspection; machine learning; fully convolutional network

1. Introduction and Objective

Bridges in Japan, especially those managed by local governments (municipalities), deteriorate over time. At the same time, the managers of the bridges in municipalities are also required to make effective inspection on bridges, because the smaller the size of a municipality is, the fewer the civil engineers in the municipality are [1]. In order to deal with the problems, an automated assistance is to assess the bridges' condition.

Automated judgement systems for some types of damage started to be developed by geometrical approaches. Chun et al. [2] proposed a semi-automatic method which is able to detect cracks from images of asphalt pavements, by manipulating images with statistical and geometrical methods. However, in order to apply automatic damage detection to bridge inspection, there still remain other types of damage which should be detected. For example, in the inspection code issued by Niigata Prefecture [3], they define 36 different types of damage which should be checked during regular inspection.

Delamination is a state where a thin cover of the concrete deck of a bridge is partially laminated from the surface of the deck (Figure 1). This is one type of damage which is defined in the Niigata inspection code. When delamination becomes worse, the rebar inside the deck is exposed (rebar exposure), which is considered to be a serious deficiency as stated in the inspection code. In order to judge delamination accurately, non-destructive evaluation such as ground penetrating radar (GPR) or infrared thermography (IR) has been proposed [4]. These technologies enable managers of expressways to specify the delamination on the top surface along their roads. However, GPR or IR cannot be simply applied to the inspection in municipalities' bridges, because these bridges scatter all around the municipality, and the location of delamination at the bottom of the bridge should be specified in the inspection.

This study aims to develop a delamination auto-detection system from photographs in inspection records by visual segmentation using Fully Convolutional Network (FCN) developed by Long (2014) [5], which visualizes the areas of delamination or rebar exposure as polygons.

Figure 1. A typical picture of delamination (with rebar exposure).

2. Materials and Methods

2.1. Dataset and Annotation

The dataset of this research consists of 416 photographs of delamination and/or rebar exposure on decks in the inspection records owned by Niigata Prefecture (in Japan). In these images, some of the delamination are in close-up, while others are zoomed out. Soundness about the severity of delamination and rebar exposure is recorded for each of all images in 4 grades (a, c, d and e), based on the inspection code provided by Niigata prefecture (Table 1).

Table 1. The criteria of judging soundness of delamination (defined in the inspection code of Niigata Prefecture (Niigata Prefecture, 2014)).

Soundness	Description
a	No damage
c	Only delamination is observed (including partial delamination)
d	Rebar inside the deck is exposed, but the rebar is not severely corroded (including partial damages)
e	Rebar inside the deck is exposed and the rebar is severely corroded (including partial damages)

For each of these photographs, annotation of the area of "concrete deck," "delamination" and "rebar exposure" is created by the students in the department of civil engineering (Figure 2). The annotation is marked as a polygon shape. Here, delamination is defined as a state where aggregate inside the concrete deck is visible, and rebar exposure as a state where an exposed rebar can be identified in the image.

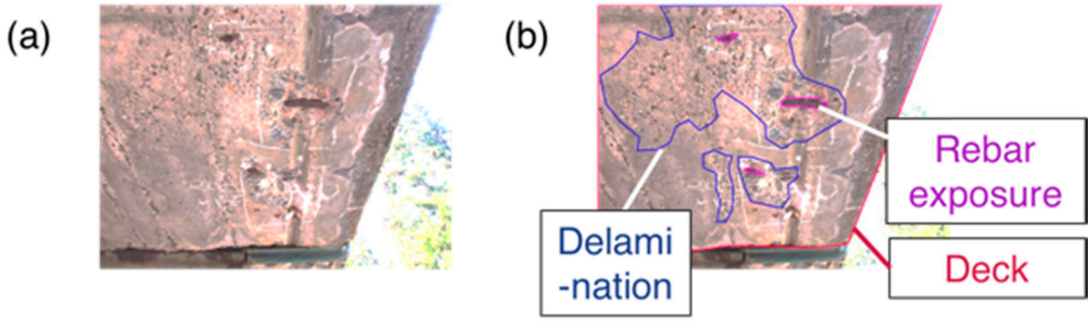

Figure 2. One of the trained images before annotation (**a**); after annotation of "deck," "delamination" and "rebar exposure" (**b**).

2.2. Fully Convolutional Network (FCN)

Fully Convolutional Network (FCN) is one of the deep learning networks for pixel-to-pixel segmentation. In this project, some images with annotation are trained for FCN in order to identify where on a concrete deck is delaminated. The 296 images are used for training, with a section outside the deck for each image trimmed off, and the rest of the 120 images are used for validation.

3. Results and Discussions

3.1. The Trend of the Result of Segmentation

The validation results of the training aided by FCN successfully showed a good agreement with the results with the naked eye (Figure 3). The FCN network succeeded in detecting the texture of delamination on the concrete deck, even if the resolution of the images is not clear enough to identify the location of the damage. The network was also able to detect rebar exposure which is just several-pixel width.

3.2. Comparison with the Ground Truth of the Actual Inspection

The segmentation results of FCN were classified into 4 categories (a, c, d and e), according to the inspection code of Niigata prefecture. The results were classified as "a" if there is no delamination or rebar exposure confirmed in the result of each image; "c" if there is delamination but no rebar exposure; "d/e" if there are both delamination and rebar exposure.

Comparing the results of FCN result with the ground truth (original classification at the inspection site), the FCN result showed 85.8 % accuracy in categorizing the damage (Table 2). It should be noted that the images with soundness "a" could not be used for validation because of the limitation of the dataset. However, the accuracy implies that the quality of the delamination detection would be enough when it is used as an assistant system together with the manual visual inspection.

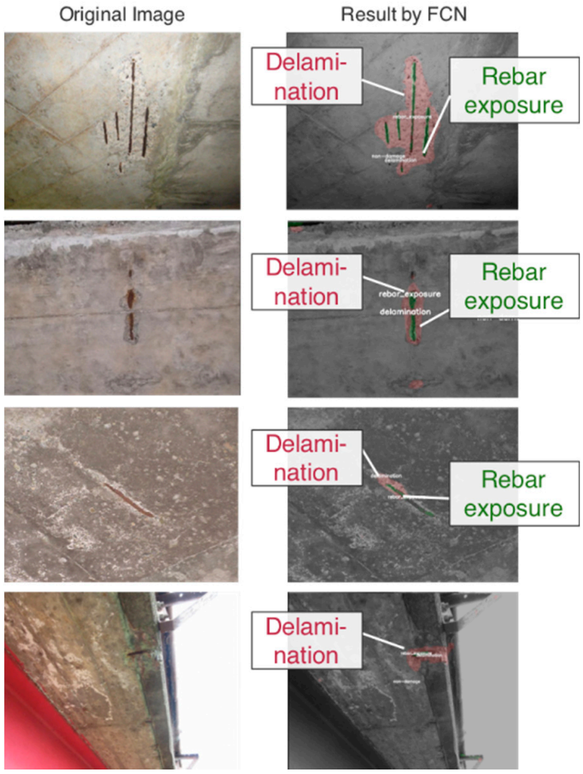

Figure 3. A part of the validation result by FCN.

Table 2. The confusion matrix between the ground truth and the judgement from the FCN result.

		The Judgement from the FCN Result		
		a	**c**	**d/e**
Ground Truth	**a**	0	0	0
	c	1	25	13
	d/e	0	3	78

4. Conclusions

In this research, the photographs of delamination in the inspections records are used as the training data for FCN, which visualize the areas of delamination and rebar exposure in the photograph. This can be a new method of delamination detection and is good at identifying the location of delamination on the bridge surface. The results indicate that the accuracy of the detection is practicable as a support for manual visual inspection in municipalities, which lack inspection engineers. Moreover, this result has implied that images in inspection records, which are not been actively analyzed for the sake of inspection or maintenance, could be the rich source of information that can improve the painful manual inspection.

5. Future Works

Although this technology is able to identify the location of delamination as a whole, the network still has several errors, e.g., an error with unidentified delamination and an error with the wrong identification of delamination (Figure 4). In order to deal with these problems, our team is now trying to increase the accuracy by enhancing both the quantity and quality of the dataset. In addition, our final goal for this project is the verification of these automated damage detection system (including other types of damage) at the inspection site, together with the application for inspection assisted by tablet PCs and unmanned aircraft.

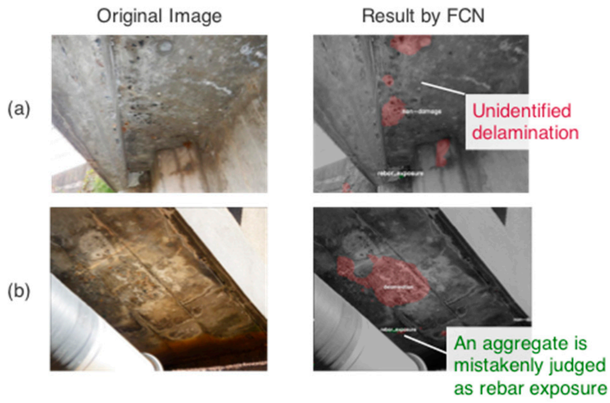

Figure 4. A part of the validation result by FCN: (**a**) wrong identification of delamination; (**b**) false positive.

Author Contributions: T.K., K.N. and J.R. designed the experiments; T.K. and K.I. prepared the dataset and annotations; T.K. and J.R. conducted the experiment; T.K., K.N., H.P. and J.R. analyzed the results; T.K. wrote the paper; K.N., H.T., H.P., and K.I. reviewed the paper.

Acknowledgements: The authors are grateful to Osama Abdelfattah Hegeir, Ahmed Okeil Mohamed Atia and Yuhga Sasaki with the annotation of the photographs. This research was supported by Council for Science, Technology, and Innovation (CSTI), Cross-ministerial Strategic Innovation Promotion Program (SIP), "Infrastructure Maintenance, Renewal, and Management Technology" (Funding agency: JST).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Annual Road Maintenance | Road Bureau, Ministry of Land, Infrastructure, Transport and Tourism. Available online: http://www.mlit.go.jp/road/sisaku/yobohozen/yobohozen_maint_index.html (accessed on 29 April 2018).
2. Chun, P.J.; Hashimoto, K. Development of semi-automatic asphalt pavement crack detection system using image processing and machine learning approach. *J. Jpn. Soc. Civ. Eng. E1 (Pavement Eng.)* **2015**, *71*, I_31–I_38.
3. The Bridge Regular Inspection Code in Niigara Prefecture [Standard Inspection] | Road Management Division, Civil Structure Department, Niigata Prefecture. Available online: http://www.pref.niigata.lg.jp/HTML_Simple/414/850/01-1_bridge-standard,0.pdf (accessed on 29 April 2018).
4. Scotta, M.; Rezaizadeha, A.; Delahazab, A.; Santosc, C.G.; Moored, M.; Graybeale, B.; Washerf, G. A comparison of nondestructive evaluation methods for bridge deck assessment. *NDT E Int.* **2003**, *36*, 245–255.
5. Shelhamer, E.; Long, J.; Darrel, T. Fully Convolutional Networks for Semantic Segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 8–10 June 2015; pp. 3431–3440.