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TOWARDS A SOLUTION FOR THE PRE-FAILURE CONCRETE ELEMENT CRACK DETECTION PROBLEM

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Abstract

Crack detection in concrete bridge elements is critical to the bridge's durability and safety. The ability to link cracks with the type of damaged element, location, and the moment of occurrence is critical for understanding the structure's behaviour. While the detection of cracks in concrete representing the failure condition is currently a relatively straightforward task, the identification of narrow cracks representing the pre-failure state has not yet received a satisfactory solution. This paper discusses a solution for segmenting structural elements on images and segmenting cracks using a deep learning network trained on a prepared dataset of pre-failure concrete cracks.

Introduction

The occurrence of cracks in reinforced concrete structures is a natural phenomenon, which in many cases cannot be avoided. In order to be able to assess whether the occurrence of cracks may affect the durability of the structure and pose a risk to its safety, it is necessary to determine the probable cause of the damage, based on factors such as the nature of the element's work, the place where the damage occurred or the time at which the damage occurred (e.g. after performing load tests). At the same time, the formation of cracks can be caused by the effects of both mechanical and environmental factors, as well as being the result of design or construction mistakes. It should also be noted that according to Eurocode 2 (CEN, 2004) the crack limit value (i.e. the value above which the serviceability limit state of the structure is exceeded) is a very small value and is 0.3mm.

For this reason, during the engineer's site inspection, these cracks may be difficult to detect by human eye, particularly in areas that are difficult to access such as pylons, spans over rivers and the inside of box girders. At the same time, the engineer inspecting the technical condition of the structure by reviewing individual elements, assessing the size of the damage, and documenting with photographs is the person who is responsible for assessing the impact of the damage on the structure's safety, and who decides on the necessary repair works or taking the structure out of service. The inspection process is labour-intensive, time-consuming and, in particular, is subject to the engineer's subjective opinion and experience. It has been estimated that approx. 50% of condition assessments are incorrect or vary depending on the engineer who performs the inspection (Hüthwohl et al., 2019).

This paper presents a solution based on machine learning algorithms that can support the engineer's work and condition assessment of structures. This solution allows for the detection of bridge structure elements on images and then the detection of cracks for a particular structure element in relation to the location of the damage. Particularly, by training a neural network based on a dataset of cracks representing the pre-failure state of the structure, the presented solution can be used to detect damage at an early stage of its occurrence. Detecting the cracks of reinforced concrete or asphalt structures representing the failure state is a relatively straightforward task in the current state of the art (Ali et al., 2022; Li et al., 2022; Nguyen et al., 2023), but identifying the pre-failure state indications in the form of very narrow cracks has not yet received a satisfactory solution. By diagnosing the occurrence of a crack at the pre-failure stage and linking it to a possible cause based on where the damage occurred, it is possible to take the necessary repair steps (e.g. protecting the damage), to monitor the development of the damage and, consequently, to extend the service life of the structure.

The first part of this paper discusses the causes of cracks in reinforced concrete elements of bridges and indicates for which elements a given cracking caused by a given factor is characteristic. The second part discusses the authors' dataset "NCCD-PF - A pre-failure narrow concrete cracks dataset for engineering structures damage classification and semantic segmentation" (Tomaszkiewicz & Owerko, 2023b). The segmentation of concrete elements of a bridge structure for which cracks are detected is presented in the third part. The fourth part, in turn, presents the solution of a deep learning algorithm trained based on the discussed dataset, for the identified structural elements.

The problem of cracks in reinforced concrete elements

The bridge condition inspection procedure varies from one country to another. The inspection procedure varies in terms of the frequency of inspections, the types of elements that need to be checked in a particular type of inspection, the value of the condition ratings of the elements. Regardless, the procedure for conducting the inspection itself is because an engineer performs an on-site inspection. In the case of damage, it is the engineer's responsibility to note this fact in the inspection protocol and to make documentation of the damage. At this stage, the engineer is required to decide whether the damage represents a risk to the bridge, whether additional expert work should be carried out and the urgency to do these works. This stage when the engineer decides whether the damage represents a risk to the structure is supported by the approach presented in this paper, in relation to concrete cracking.

Cracking in reinforced concrete structures is a natural phenomenon, which in many cases cannot be avoided. In order to be able to assess whether the occurrence of cracking may affect the durability of the structure and pose a risk to its safety, it is necessary to determine the probable cause of the damage, based on factors such as the nature of the given structural element's work, the place where the damage occurred or the time at which the damage appeared (e.g. after carrying out test loads on bridges).

Among the most characteristic cracks that occur in reinforced concrete elements, we can point out (Tomaszkiewicz & Owerko, 2023a):

- Cracks caused by the compression of a reinforced concrete element - in particular abutments, pillars
- Cracks caused by the excessive bending moment stress - especially in girders, in zones of extreme bending moment
- Cracks caused by nonuniform settlement of supports in particular abutments, pillars, foundations
- Cracks due to plastic shrinkage - especially observed for bridge slabs, pedestrian paths, concrete pavements
- Cracks in prestressed elements caused by corrosion of tendons, corrosion of tendon anchorages - characteristic for girders or anchorages of cable elements suspending the superstructure.

A particular type of cracking occurring in bridge structural elements is that of massive elements such as foundation slabs, abutments, pillars and pylons. The massiveness of a structural element can be defined as the ratio of the surface area of the element to its volume. In the process of cement hydration during concrete setting, the ratio of the surface area (i.e. the area through which the heat of hydration is removed) to the volume in which it is emitted is small. These cracks already appear during the construction phase, i.e. when the concrete strength is significantly lower than the design strength and when the bridge structure is not yet operating under full-service load. In addition, under further loading, cracks may propagate through the entire thickness of the concrete, resulting in a loss of structure monolithicity and a change in its static scheme.

The link between the type of structural element, the location of the damage and the causes of the damage will be discussed using the example of an abutment of a bridge structure. As a result of the cement hydration process, the temperature inside a concreted abutment rises to a maximum and then decreases to equalise with the ambient temperature. This results in tensile stresses that exceed the strength of the 'young' concrete. At the same time, the development of shrinkage phenomena occurs, resulting in cracking of the element. During the heating phase, the central part of the element heats up to a higher temperature than its edge, which causes the edge zones to be stretched. In the cooling phase, the central part of the element shrinks to a higher temperature than the edge, which causes stretching of the central zone of the element. Abutment walls are the elements in which the deformation of the lower edge is limited by external constraints. Abutment walls are concreted after the foundation has hardened and cooled, hence the curing of the wall takes place when the bottom of the wall is restrained in the foundation and there is no possibility of deformation. Therefore, thermal-shrinkage cracks of abutments are vertical cracks that begin above the abutment wall-foundation interface and disappear at the top of the abutment wall.

Description of the dataset for pre-failure cracks in concrete elements

The dataset developed by the authors "NCCD-PF - A pre-failure narrow concrete cracks dataset for engineering structures damage classification and semantic segmentation" (Tomaszkiewicz & Owerko, 2023b) has been made available as an open dataset and described in detail in the publication (Tomaszkiewicz & Owerko, 2023a). This dataset is dedicated to the problems of classification and segmentation of reinforced concrete element cracks. One of the dataset's characteristics is that it only represents those cracks which do not exceed a width of 0.3mm. This value is defined in EC 1992-1-1 (CEN, 2004) as the limit value of a crack with respect to typical construction methods for engineering elements and the conditions under which they operate. The crack detection using the algorithm trained on the presented dataset therefore allows the detection of cracks at the pre-failure stage. In addition, the dataset is characterised by the presence of a complex concrete surface finish (Figure 1), which can significantly influence to the results of the machine learning algorithms. The dataset's characteristic concrete surface complexity is shown in Figure 2.

The images that compose the dataset have been differentiated by:

- The type of element on which the cracks occurred (e.g. abutment, pillar, concrete barrier, tunnel wall)
- The cause of the cracks (e.g. thermal and shrinkage stresses in young concrete)
- Stage in the life cycle of the structure at which the image was obtained (from the construction stage to the operational stage)
- Quality of the reinforced concrete element construction, its maintenance and conservation.

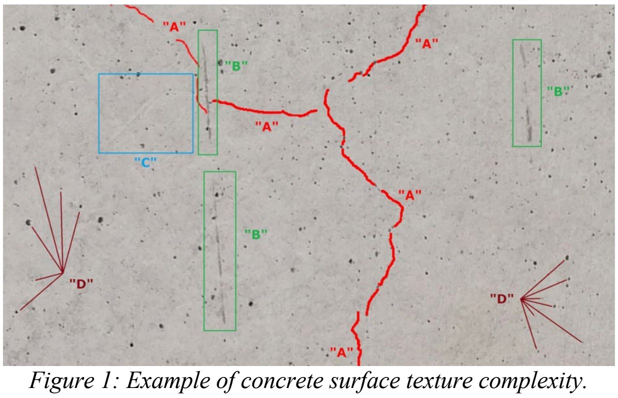


Figure 1: Example of concrete surface texture complexity. Marked as: "A" - cracks, "B" - dirts, "C" - mechanical damage, "D" – potholes (*Tomaszkiewicz & Owerko, 2023a*)

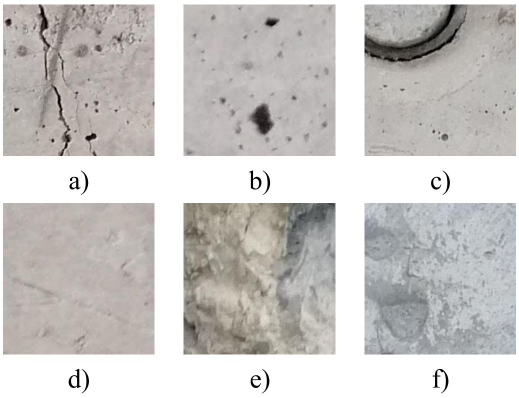


Figure 2: Example of concrete surface texture complexity, where a) dirt, b) bugholes, c) formwork marks, d) mechanical damage e) background obstructions f) troweling marks (Tomaszkiewicz & Owerko, 2023b)

The method of data acquisition for the dataset construction was chosen in such a way that the data acquired corresponds to the conditions under which bridge inspections are conducted. The images were obtained from cameras, without prior conditioning.

The dataset development started with the preparation of segmentation masks. An example of an image and its corresponding segmentation mask is shown in Figure 3 and 4. The images prepared in this way were segmented into sub-images of 224x224 pixels. On their basis, a classification dataset was created, examples of which are shown in Figure 5 (images of cracked concrete) and Figure 6 (images of uncracked concrete), respectively. The size of the dataset is shown in Table 1.

Figure 3: Example of image and corresponding segmentation mask (white pixels - crack, black pixels – background)

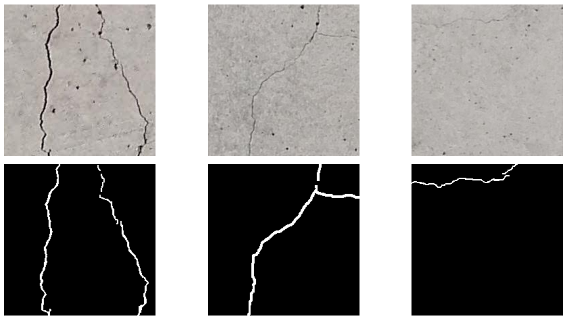


Figure 4: Example of subimages and corresponding segmentation masks (Tomaszkiewicz & Owerko, 2023b)

Figure 5: Example of cracked concrete images (Tomaszkiewicz & Owerko, 2023b)

Figure 6: Example of uncracked concrete images (Tomaszkiewicz & Owerko, 2023b)

Table 1: Number of images in the „NCCD-PF - A pre-failure narrow concrete cracks dataset for engineering structures damage classification and semantic segmentation" dataset (Tomaszkiewicz & Owerko, 2023a)

	Dataset for image classification	Dataset for image segmentation
Number of images	5388	5388
	Including:	
	Cracked – 668	
	Uncracked – 4720	

Crack location based on segmentation of the structural element on images

To preserve the link between the bridge structure element and the damage, it is possible by segmenting an image of the single structural elements of the bridge structure and then providing data about a specific element as input information for a solution based on deep machine learning networks. For this purpose, the authors adapted the SegmentAnything algorithm (Kirillov et al., 2023) for iterative segmentation of bridge structure elements. Images identified as a structural element of a specified class are then segmented into sub-images and entered into a neural network. As a result, once the concrete surface cracks have been segmented using a deep learning algorithm, it is possible to link this damage to the element on which it occurred. Using this approach, a crack image of a given structural element is obtained, with the identification of those cracks that may pose a risk to the structural element and should be monitored and those that can be considered as neutral phenomena. An example of segmentation of reinforced concrete bridge elements is shown in Figure 7.

Figure 7: Results of bridge element segmentation

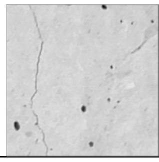
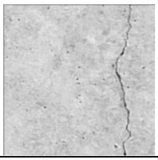
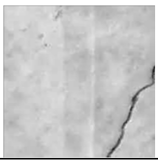
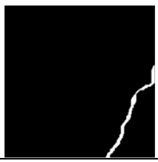
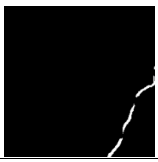
Crack detection solution using deep machine learning

Previous authors' experience (Tomaszkiewicz & Owerko, 2022) has shown that using networks trained on datasets for cracks with larger widths and fine-tuning them is not a proper solution for obtaining correct segmentation of cracks with widths below 0.3mm. The authors have developed a dedicated solution for pre-failure crack segmentation. The computer implementation was done using the PyTorch library.This solution used a modified and adapted UNet architecture originally proposed by (Weng & Zhu, 2015). The individual components of the network such as activation layers, convolution blocks etc. were implemented manually, the networks available in the PyTorch library were not used.

The network training process was based on a subset of 791 images from the presented dataset. The image size adopted for analysis was 224x224 pixels, which is also the original size of the images in the developed dedicated dataset. The images were randomly divided into a training and validation dataset in a ratio of 80:20. The dataset was divided into a batch size of 16 and trained for 125 epochs.

The results obtained, presented in Table 2, showed a high match between the network's prediction and the segmentation masks derived from the dataset. The information extracted in this way is sufficient information to be included on the image of the whole structural element and be used to assess its technical condition.

Table 2: Segmentation result using a trained deep learning network

Image	Label	Prediction
		
		
		

Limitations and future work

The presented deep learning solution covers one architecture that is effective for this problem but is not a most recent type of architecture (such as transformers). Furthermore, a problem that exists worldwide is that the amount of publicly available datasets related to the detection of different types of objects is severely limited. Data is not collected in a structured way, regarding FAIR Principles (Wilkinson et al., 2016).

Further research should be conducted in such a way that good quality datasets for deep learning algorithms can be built partly automatically. The procedures for performing bridge inspections should be developed or adapted in such a way that they meet the requirements for conducting inspections, but also allow the collecting of structured data that can be used for training deep learning algorithms. An important direction is also to conduct tests on different types of concrete mixes, keeping in mind the different potential causes of cracking. It may be helpful here to link the computational model to the location of damage in the structure, e.g. as a result of excessive loads). Such data can provide support for research related to the application of recent deep learning architectures based on multi-dimensional data as a source of knowledge (including consideration of IFC class, observation history from IoT sensors).

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