

Machine learning based NDT Data Fusion to detect Corrosion in Reinforced Concrete Structures with Inspection Data

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ABSTRACT

The key idea is to deliver an automated, machine-learning (ML) based algorithm to combine the results from different non-destructive testing (NDT) measurements on a reinforced concrete wall in order to generally improve the reliability of the corrosion assessment. To this aim, a set of data was acquired with various NDT methods. The data include concrete cover measurements, half-cell potential mapping data, electrical resistance measurements (Wenner probe) in different grid sizes, and images from the concrete surface.

After registration and preprocessing (interpolations and feature scaling), a ML algorithm was applied to cluster the data into groups. The aim was to examine the outcome of ML in comparison to traditional data analysis with manual cross-links between the individual measurements to locate corrosion damages such as cracks or cross-sectional due to chloride-induced corrosion. The surface images were analyzed by a convolutional neural network trained beforehand for the classification task (concrete crack/no concrete crack on the surface) to gain an additional numerical feature. The actual corrosion state of the reinforcement (ground truth) was examined at several locations. The preliminary outcomes of the ML are comparable to the traditional method.

Key words: Reinforced concrete, Inspection, Machine Learning, potential mapping, corrosion, NDT

INTRODUCTION

Importance of corrosion inspections

The corrosion assessment of structures in reinforced concrete (RC) will become more and more important in the coming decades. This is because our infrastructure is constantly ageing, which increases the risk for gradual deterioration. The age distribution of civil engineering structures in most industrialized countries reveals that most structures were built between 1960 and 1980 and that the average age of almost 50 years was reached in 2020. The expected related increase in number of structures needing repair is of the order of a factor between 2 to 4 in the next 20 years based on an analysis in the Netherlands.¹

In order to operate the large stock of infrastructure in an effective manner considering economical, safety, environmental and social aspects, there is a need to increase the accuracy, repeatability of analysis and the reliability of general inspections while maintaining acceptable inspection costs. An outcome of those regularly performed assessments is the basis for engineers to choose the most appropriate maintenance strategy on a case by case basis.

Corrosion of the steel reinforcement is the most prevalent cause of premature deterioration of RC structures. Furthermore, chloride-induced corrosion can cause severe damage before any visual signals are visible along the concrete surface such as rust stains.^{2,3}

The correct analysis and evaluation of different measurements with several non-destructive testing (NDT) methods is an important part of condition inspection before taking following actions such as destructive measurements.

Machine learning-based analysis of non-destructive inspection data

The recent growth in the field of ML made those models available in other disciplines such as civil engineering with user friendly application programming interfaces and highly optimized code for fast data processing. In a previous study on the usage of ML for the analysis of multi-sensor NDT data to locate chloride-induced corrosion it was concluded that supervised learning algorithms outperform individual sensor data analyzed according to valid standards in the detection of corrosion in a variety of controlled environmental condition.⁴ This study indicated that ML algorithms might be a useful tool in the future for efficient data analysis. However, the work was limited in terms of a well-controlled laboratory condition under accelerated corrosion and does not include visual features as an additional input like images of the surface.

The detection of various concrete surface damages on images with the help of convolutional neural networks (CNN) has been described in various publications as shown for example in ⁵. The existing literature on the detection of surface damages is extensive and focuses on the detection of cracks of various extents and the estimation of the crack properties such as crack width and crack length. To date, some researchers are publicly sharing their valuable data sets, since acquiring such a data set is a laborious task. Those results demonstrated the success of applying CNN for the detection of cracks with high prediction accuracies. Overall, most of these research articles only consider images as data and do not include other sensor data from NDT devices or results from destructive analyses for further data analysis.

The use of ML for the corrosion assessment of structures or the corrosion detection has not yet been widely studied on engineering structures. This paper makes an attempt to use common ML models to detect localized corrosion damages on the reinforcement on a data set from a reinforced concrete wall. Several common NDT-testing methods were applied in combination with visual inspection, namely by considering the presence of concrete surface cracks. Finally, the concrete cover was removed at selected locations to visually access the corrosion state of the steel reinforcement for a comparison to the predictions made by the algorithm. This procedure will allow determining in the future the locations for destructive testing already on-site or can be used as immediate analysis during the capturing of data with fully automated inspection robots.

EXPERIMENTAL PROCEDURE

Data set generation

The data utilized in this study was acquired in October 2019 on the wing wall of a pre-stressed bridge. The bridge was constructed in 1968 and was a former part of the Swiss highway network. In 2020, the structure was demolished and replaced with a new bridge. The acquired data consists of images of the concrete surface, electrical resistance measurements with the Wenner probe, half-cell potential measurements, and concrete cover depth measurements. Potential mapping is a well-known and established measurement method to locate corroding rebars. Nevertheless, the interpretation is not straightforward and half-cell potential data should be interpreted with additional measurements by specialist engineers⁶.

The grid with the highest point density is $10 \times 10 \text{ cm}^2$ and the area of interest was 730 cm long and 150 cm high.

After the measurements, a few selected spots the actual condition of the reinforcement were visually analyzed after manual removal of the cover concrete.

Images from the concrete surface

Concrete surface images were acquired with a Sony RX10MII SLR-camera with an image resolution of 20 Megapixels. The pictures were shot with the support of a tripod about 2.2 m from the concrete surface away at 4 positions along the wing wall perpendicular to it. Figure 1 shows the combined image of the wall.

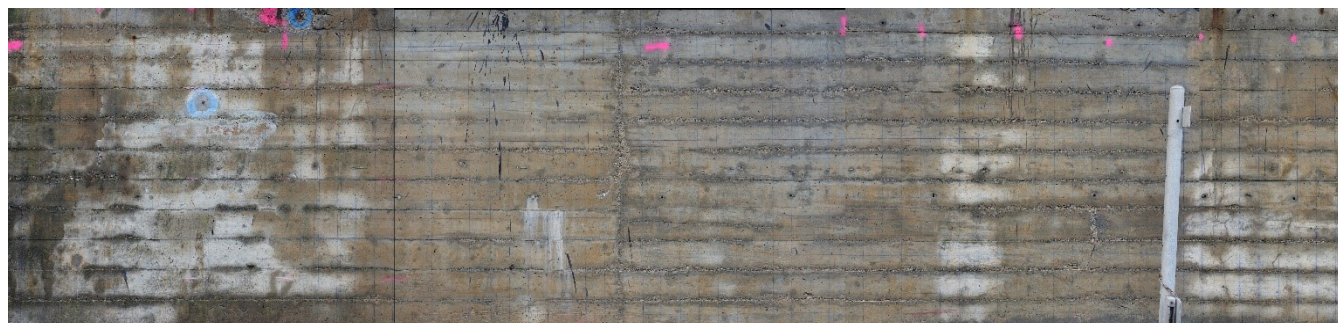


Figure 1: The combined image of the wall ($730 \times 150 \text{ cm}^2$) before splitting into parts of $10 \times 10 \text{ cm}^2$ to further process the images with the CNN.

Electrical resistance

Within a grid spacing of $50 \times 50 \text{ cm}^2$, the electrical concrete resistances were measured with a Wenner probe.⁷ The spacing between the individual electrodes was 30 mm and the 4 electrodes were positioned on the surface with an inclination of 45° against the orthogonal steel reinforcement. The resistance was measured with a measuring frequency of 107 Hz and an applied voltage amplitude of about 40 V. A total of 63 measurements was taken. The ambient air temperature was around 14°C . The tips of the electrodes that were in contact with the concrete surface were wetted from time to time with tap water.

Half-cell potential measurement

The potentials of the embedded steel reinforcement were measured with a tailor-made reference electrode of the type Copper/Copper-sulfate. The potential difference was acquired within a grid spacing of $10 \times 10 \text{ cm}^2$ with a Canin+^(†) corrosion analysis system. The grid was manually marked with blue chalk lines. The values were manually accepted after establishing contact for a few seconds. The sponge on the tip of the electrode was kept moist with tap water. The electrical connection to the reinforcement was

ensured by drilling (diameter = 4 mm) into exposed reinforcement bars and connecting cables with plugs. The electrical continuity of the reinforcement was checked at three locations prior to half-cell potential mapping.

Concrete cover measurements

The concrete cover was analyzed with a Proceq Profometer 650 AI ^(†). The horizontal reinforcement was measured with a spacing between the individual lines of 50 cm, whereas the spacing in the perpendicular direction was 20 cm. After the measurement, the data was uploaded to a computer and processed with the software from the producer of the cover meter using neighboring rebar correction with artificial intelligence (NRC AI).

Machine learning approach – Preparation of data for data fusion

The data fusion for machine-learning applications together with preprocessing is a crucial part. In this particular case, the different measurements were due to several reasons measured with different point densities. Nonetheless, the handling of this data is much simpler, if at each location measurement data is available. Hence, in this study, missing measurements were estimated based on interpolation algorithms or engineering judgment. Table 1 gives an overview of the individual measurements, the type of measurement, and the applied processing before ML was applied.

Table 1
Overview of the preparation of each measurement to reach a similar measurement grid for further processing.

Measurement	Grid [cm x cm]	Measurement type	Processing steps before the machine-learning algorithms
Surface image	170 x 180	Image	Manual image stitching, cut to pieces, CNN
Potential mapping	10 x 10	Point	None
Electrical resistance	50 x 50	Point	Linear interpolation to a grid of 10 x 10 cm ²
Concrete cover	50 (horizontal), 20 (vertical)	Line	Extraction and the minimum cover were taken, Manual extrapolation

Images from the concrete surface

The images from the concrete surface were slightly rectified along the grid of the potential reading and manually combined to a single image with a final resolution of 12034 by 2860 Pixels as shown in Figure 1. Afterward, the combined image was cut along the grid of the potentials and cut into pieces of roughly 10 x 10 cm² concrete surface. After this processing step, the images had a size of about 170 x 170 pixels, with 73 images in the horizontal direction and 14 images in the vertical direction. As a next step, a CNN was applied.

Since the training of large CNN may take up a significant amount of time depending on numerous factors such as the input size for the CNN, the amount of layer, the number of epochs during the training and the computational power. For the current problem, a pre-trained VGG-16 for an image classification task was used as a base for transfer learning in python with the deep learning library Keras.⁸ The training was done in two consecutive steps whereas for the second steps more layers of the CNN were unfrozen during the training process. The training data set and the validation consisted of a total of 40'000 images that were taken from Dorafshen et al.⁹

Afterwards, the 10 x 10 cm² images of the structure were analyzed with the CNN to predict if a crack was present or not within each image. Figure 2 presents the prediction of the crack probability with CNN of the individual parts of the complete image. The average value of the crack probability was 47.5% with the lowest value of 1.89% and a maximum value of 98.0%. Once the predictions of the neural network

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