3D Corrosion Detection in Time-dependent CT Images of Concrete

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Abstract
In civil engineering, the corrosion of steel reinforcements in structural elements of concrete bares a risk of stability-reduction, mainly caused by the exposure to chlorides. 3D computed tomography (CT) reveals the inner structure of concrete and allows one to investigate the corrosion with non-destructive testing methods. To carry out such investigations, specimens with a large artificial crack and an embedded steel rebar have been manufactured. 3D CT images of those specimens were acquired in the original state. Subsequently three cycles of electrochemical pre-damaging together with CT imaging were applied. These time series have been evaluated by means of image processing algorithms to segment and quantify the corrosion products. Visualization of the results supports the understanding of how corrosion propagates into cracks and pores. Furthermore, pitting of structural elements can be seen without dismantling. In this work, several image processing and visualization techniques are presented that have turned out to be particularly effective for the visualization and segmentation of corrosion products. Their combination to a workflow for corrosion analysis is the main contribution of this work.

Keywords: concrete, corrosion detection, 3D computer tomography (CT) imaging, image processing, visualization

1. Introduction

To better understand the damages caused by corrosion processes, reinforced concrete specimens are analyzed non-destructively by means of 3D CT imaging. Non-destructive testing allows testing of the same specimen after several pre-damaging steps with subsequent imaging to reveal the internal damaging over time. The degree of damaging due to chloride-induced corrosion can be measured temporally and spatially. Results of electrochemical investigations at reinforced concrete specimens are used for comparisons, although such methods are not able to localize pitting corrosion resp. corrosion products at the rebar [8].
1.1 Related Work

Investigations on the damage processes of reinforced concrete have been carried out for a long time. Mainly electrochemical methods are used for non-destructive investigations. These methods result in the measurement of mass reduction and corrosion rate over time [2]. To reveal the spatial distribution of corrosion products inside concrete, these methods are not appropriate. Furthermore, it is not possible to show possible dependencies of the inner structure of concrete (pores, cracks, rebars, mortar and aggregates). Most of the publications on the rate of corrosion are based on destructive testing of concrete specimens with photographic or gravimetrical methods. Specimens can, with those methods, only be tested once and comparisons over time are only possible using several specimens, which introduces an additional source of uncertainty.

The use of 3D computed tomography images for non-destructive testing of concrete [1][3][7] has increased recently, which not only reduces the number of specimens needed but also has the advantage of improved visualization. 3D CT images allow the detection of corrosion over time in the same specimen and its spatial resolution starting from an initial state. Despite these obvious advantages, the usage of 3D CT images to detect and analyze corrosion products in reinforced concrete has not been published before to the best knowledge of the authors.

2. Experimental Procedure and Data Acquisition

For the tests presented in this paper, two specimens with a large artificial crack and a steel rebar were manufactured [Fig. 2 left]. Here, the artificial crack provides a targeted way of inducing chlorides directly to the rebar to initiate faster corrosion processes inside the concrete. After curing and drying of the concrete, a first 3D CT image was taken, which is defined as the initial state. Following this, three cycles of electrochemical damaging through chloride induction together with an electrochemical polarization at the rebar were carried out. The first damaging cycle includes 72 hours, the second was finished after 144 h and the third after 456 h. After each damaging cycle, a 3D CT image of the specimen was acquired. The positions of the specimens were carefully kept as stable as possible during CT imaging.
After the period of artificial damaging and imaging, four time-dependent datasets of each of the specimens representing the initial state and three levels of damage were available for further investigations.

For all CT measurements, an anode voltage of 200kV was used. To reduce beam hardening, a 0.5mm Cu- and a 0.75mm Ag-prefilter was used. The dimensions of the reconstructed CT images are 2031 x 2031 x 627 (8 bit) with a voxel size of 32 µm x 32 µm x 32 µm. All further investigations were carried out using Amira ZIB Edition [12] for segmentation, evaluation and visualization. These investigations were applied to a cropped subset of the datasets containing the most important parts of the data without the surrounding background.

3. Time-dependent Segmentation of Corrosion Products

For humans, it is easy to differentiate between materials as illustrated in Fig. 3, especially if they are trained to inspect such images routinely. Steel rebar, mortar, crack, pores and the corrosion products are clearly discernible due to different grey values.

An automatic segmentation by means of global thresholds, however, did not lead to sufficient results, because the grey values vary a lot. Corrosion products with a low density as well as with a high density and corresponding low and high grey values can be found within big cracks and pores. Their shapes are often diffuse without perceptible material boundaries.

Taking texture features into account like contrast, dissimilarity and entropy [9][11], also did not lead to satisfying results, because there are no significant differences between the materials that can be used for automatic segmentation.

Much better results in automatic segmentation can be achieved by using prior knowledge. In case of time-dependent image series, the first image, the initial state, and its segmentation can be used as prior knowledge. A semi-automatic segmentation of that initial state can

![Figure 3: Slice through 3D CT dataset with clearly recognizable corrosion products inside the crack, near to the rebar and in bigger pores](image)
be carried out easily, because there are no detectable corrosion products. The big cracks and pores as well as the steel rebar can be segmented mostly using thresholding. If global thresholding led to unsatisfying results, flooding starting from manually given seed points was used. The remaining parts can then be regarded as the cement matrix. All later states are then registered to the initial state with rigid registration as a prerequisite for further segmentation. The segmentation of the initial state (background, big cracks and pores only) is then copied to all other subsequent states. The detection of corrosion products can then be carried out by computing the differences in grey values between subsequent states per segment. Due to pitting, the volume of the steel rebar is decreased and the steel is substituted by corrosion products (Fe$_2$O$_3$ and Fe$_3$O$_4$), which results in a lower grey value in the rebar area compared to previous states. In all other segments (materials), the corrosion leads to higher grey values as before. Another prior information is that the formation of corrosion products always starts near to the steel rebar and propagates into the surrounding material. This information can be exploited for the segmentation of corrosion in non-time-dependent datasets, but it is not used in the presented approach, because it led to less reliable results.

The following workflow has proved to be acceptable for corrosion detection in time-dependent CT datasets:

1. Rigid registration of the datasets to the initial state including resampling to a common grid regarding the voxel size.
2. Semi-automatic segmentation of the big cracks, pores and the cement matrix of the initial state and copying this segmentation to all subsequent datasets.
3. Threshold-based segmentation of the steel rebar in all datasets independently.
4. Computation of voxel-based differences in the crack, pore and cement matrix segments. Labeling as corrosion products if the differences lie inside a given range.
5. Computation of voxel-based differences in the rebar segment. Labeling as corrosion products if the differences lie inside a given range which is different from 4.
6. Combination of the results of steps 4 and 5.
7. Morphological smoothing of the segmentation result leading also to a removal of small connected components.

All segmentations are voxel-accurate. Subvoxel accuracy does not seem to be practicable, because the segment boundaries are very sensitive (except the steel rebar) with respect to the grey values.

4. Evaluation and Results

4.1 Comparisons between automatic and manual segmentations

Since there was no real ground truth segmentation of a whole dataset to be compared with, the grey values that indicate corrosion products were determined empirically by probing the grey values on some slices with respect to the segments. A manual segmentation was performed later by experts on a few slices only and was then used for comparisons.

Visual comparisons of the manual segmentation with the automatic one (Fig. 4) often showed better results for the automatic segmentation. A visualization of a classification [5] of the comparison results (true/false positives/negatives) is shown in Fig. 5. A reason for the
differences between the segmentations might be the veil-like shape and transparency of corrosion products especially inside the big crack, where it is difficult to identify material boundaries. This also indicates the uncertainty of such segmentations. However, applying the same parameters to the automatic segmentation of different datasets yields comparable result, which is an advantage to manual segmentation, although the results would never be perfect.

Figure 4: Comparison between automatic segmentation (left) and manual segmentation (right). Corrosion products are depicted in red

Figure 5: Comparison between manual and automatic segmentation. Red: Corrosion segmented manually and automatically (true positives), Green: automatically detected corrosion not segmented manually by experts, Turquoise: manually segmented, but not segmented by automatic corrosion detection
4.2 Visualization

The most appropriate visualization methods for such kind of data seem to be 1D plots and 2D slicing through the datasets while mapping the segmented corrosion products to colors. The reference volume of the rebar (Rebar_0) and the volume for three levels of damage along its longitudinal axis (Slice) are shown in Fig. 6. Computing the integrals of the curves results in the total volume of the rebars per time step. It can be used to quantify and compare the decrease of the rebar volume due to pitting corrosion over time. The results correspond with results from gravimetric measurements of mass reduction processes. Fig. 7 depicts the effect of pitting over time in three levels of damage where the large crack touches the rebar. Here the grey values in the areas labeled as corrosion are mapped to colors representing the density of corrosion products.

![Figure 6: Decrease of the rebar volume for all levels of damage over all slices (white: initial state = Rebar_0, blue: highest level of damage = Rebar_3). The large crack touches the rebar in the range between the vertical yellow lines](image)

3D visualizations like isosurfaces of the steel rebar (Fig. 8) depict the spatial distribution of damages. They resemble images from dismantled specimen of destructive testing methods.
4.2 Statistical evaluation

After segmentation of the corrosion products, a statistical evaluation was performed. To compute the percentage of corrosion depending on the distance to the rebar, a distance field to the center of the rebar was calculated (Fig. 9). Then the percentage of a certain distance range to the total amount of corrosion products was computed and is shown for one specimen in Tab. 1.

![Figure 8: 3D visualization of pitting with isosurfaces of the rebar (left to right: increasing levels of damages)](image)

![Figure 9: Evaluation of corrosion products with respect to the distance to the rebar center. Range 7-8 mm highlighted](image)

<table>
<thead>
<tr>
<th>Distance range (mm)</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 - 4</td>
<td>0</td>
<td>0</td>
<td>0,4</td>
</tr>
<tr>
<td>4 - 5</td>
<td>36,6</td>
<td>32,4</td>
<td>38,5</td>
</tr>
<tr>
<td>5 - 6</td>
<td>27,7</td>
<td>22,5</td>
<td>23,6</td>
</tr>
<tr>
<td>6 - 7</td>
<td>10,5</td>
<td>10</td>
<td>8,3</td>
</tr>
<tr>
<td>7 - 8</td>
<td>5,5</td>
<td>8,3</td>
<td>6,7</td>
</tr>
<tr>
<td>8 - 9</td>
<td>4,9</td>
<td>6,3</td>
<td>5,6</td>
</tr>
<tr>
<td>9 - 10</td>
<td>4</td>
<td>5,6</td>
<td>5,1</td>
</tr>
</tbody>
</table>

Table 1: Corrosion products in % with respect to the distance to the rebar center for all three damage levels
A mapping of the grey values to colors in regions labeled as corrosions shows that the density of corrosion products is high especially in regions of pitting (Fig. 10). A statistical evaluation of the density for the whole datasets is listed in Tab. 2.

The differences in percentage of corrosion products at each density level are based on the different damage duration and the formation of oxide levels. In all areas, excluding the crack, a diffusion resistance may regulate the oxidation speed of the corrosion products.

Table 2: Percentage of corrosion products with respect to the density levels for all three damage levels. It should be noted that density is not a density in its usual meaning, but a graduation of grey values.

<table>
<thead>
<tr>
<th>Density level of corrosion products</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>29,3</td>
<td>16</td>
<td>14,3</td>
</tr>
<tr>
<td>2</td>
<td>26,3</td>
<td>42,1</td>
<td>32,5</td>
</tr>
<tr>
<td>3</td>
<td>12,5</td>
<td>18,2</td>
<td>17,8</td>
</tr>
<tr>
<td>4</td>
<td>14,4</td>
<td>12,2</td>
<td>17</td>
</tr>
<tr>
<td>5</td>
<td>13,5</td>
<td>5,3</td>
<td>11,6</td>
</tr>
<tr>
<td>6</td>
<td>2,9</td>
<td>3,7</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>2,5</td>
<td>2,9</td>
</tr>
</tbody>
</table>

The distribution of the corrosion products within different materials resp. regions is shown in Tab. 3. It looks like a stable formation of corrosion products in the range of the crack, but it is a decreasing formation due to different damaging durations (level 1 = 72 h, level 2 = 72 h and level 3 = 312 h) of electrochemical polarization, which prevents a direct comparison of the measured values. When looking to the step from damaging level 2 to 3 over time, one observes a massive reduction at the formation of corrosion products. This is due to an electrochem-
ical isolation of the pitting corrosion by the formation of corrosion products of high density. The migration of Fe is hindered by corrosion products with high density. Those kinds of corrosion products also have a great influence to the electrochemical measurements, since it is impossible to measure and locate active corroding parts later on.

Table 3: Corrosion products in % with respect to the material for all three damage levels

<table>
<thead>
<tr>
<th></th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pores</td>
<td>10,9</td>
<td>9,9</td>
<td>9</td>
</tr>
<tr>
<td>Crack</td>
<td>38,5</td>
<td>41,5</td>
<td>33,5</td>
</tr>
<tr>
<td>Steel Rebar</td>
<td>32,3</td>
<td>21,7</td>
<td>33</td>
</tr>
<tr>
<td>Other</td>
<td>18,3</td>
<td>26,7</td>
<td>24,6</td>
</tr>
</tbody>
</table>

All tables show results of an evaluation of the data measured and segmented from one of the specimens. Therefore the results cannot be taken as common for other specimen, whereas the methods introduced can be applied to any other specimen provided that the testing and imaging is done as described here.

5. Conclusions and Future Work

The previous chapters described the artificial damaging applied gradually to reinforced concrete specimen and the 3D CT imaging taken in between, where the first image is taken prior to the artificial damaging and regarded as the initial state. The subsequent time-dependent 3D images are then registered to the initial state. This was followed by a semi-automatic segmentation of cracks, pores and the rebar. Using this segmentation, an investigation of the propagation of corrosion products over time could be performed by means of standard image processing algorithms. The results were then visualized and evaluated statistically.

It could be demonstrated that the combination of well-known image processing methods can be used to segment and evaluate time-dependent 3D CT images of reinforced concrete specimens to perform and assess corrosion measurements.

The electrochemical results (see above) and the results depicted in tables 2 and 3 reveal that the formation of corrosion products have a massive influence to electrochemical investigations. Without the combination of 3D CT images together with electrochemical investigations, the results would be interpreted as passive corrosion systems.

In future investigations, we will perform corrosion measurements with defined anodic areas. For that we will locate anodic parts like pitting corrosion by using 3D CT imaging. Initial tests have shown that it is possible to recognize the surface of the pits and calculate the current density without using an integral of the electrode surface. This implements the opportunity for the first time to calculate a specific anodic current density and other electrochemical parameters without destroying the concrete specimen.

References


