MACHINE LEARNING FOR THE DETECTION OF CRACKS IN CONCRETE – DEALING WITH OBSTACLES IN COMBINING 2D MICROSCOPY AND 3D COMPUTED TOMOGRAPHY

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1. Introduction

The microstructural details of concrete are essential toward understanding and improving their material properties for different applications in civil engineering. Cracks influence the mechanical properties and enhance damage processes by providing transport routes for moisture and liquids. Imaging techniques such as computed tomography (CT) and microscopy are particularly well suited for the exploration of crack structures. CT has the advantage of generating 3D data sets, but the resolution is significantly limited. Conventional microscopy produces high-resolution data, but only 2D. The case study presented will show how data sets are generated and segmented. Thereafter, the information from both methods is combined to produce a high-resolution overall dataset.

2. Materials and Methods

Cylindrical concrete specimens (height 75mm; diameter 50mm) containing different aggregates were produced for the studies. The specimens were treated with several freeze-thaw cycles to produce cracks without destroying them. Computed tomography scans were performed with phoenix nanotom|m and reconstructed with the accompanying software datos|x. The registration in the coordinate system as well as the improvement of brightness and contrast were performed using VG Studio MAX. The next steps were done with the use of the opensource Software Fiji. For the beam hardening correction the plugin of Carla Romano [1] was used. The segmentation of the datasets was done by machine learning implemented in the Trainable Weka Segmentation (TWS) tool. The CT-imaging was followed by preparation of the thin sections for 2D microscopy. To increase the contrast, the thin sections were impregnated with color pigmented fluorescent epoxy resin. The 2D imaging was done by using BX43 (Olympus) and Stream. Segmentation was also performed using the Fiji TWS tool. For the combining of 2D and 3D results, we compared the possibilities offered by Fiji and Slicer.

3. Results and Conclusion

Algorithm based determining the position of 2D microscopy images in a 3D CT dataset is challenging at different points. The different representation of the individual image contents (aggregate, air, cement paste) and the different resolution cause problems. We achieved the best results with manual registration. However, the quality depends on how experienced the user is. A semi-automatic and thus user-independent combination of the two imaging methods works better if the data sets are first segmented independently and then merged. This works very well with Fiji, but a range of expert knowledge about machine Learning is required. For inexperienced users, we recommend Slicer 3D, which is more intuitive to use, but works more reliably for much smaller data sets in our experiments.

4. Acknowledgements

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5. References

[1] C. Romano et al (2019). Automated high accuracy, rapid beam hardening correction in X-Ray Computed Tomography of multi-mineral, heterogeneous core samples. Computers & Geosciences, 144-157.https://doi.org/10.1016/j.cageo.2019.06.009