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4D EARLY AGE CEMENT HYDRATION ANALYSIS BY PTYCHOGRAPHIC X-RAY COMPUTED TOMOGRAPHY AND MACHINE LEARNING SEGMENTATION

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1. Introduction

Cement manufacturing is responsible for ~7% of the anthropogenic CO_2 emissions and hence, decreasing the CO_2 footprint, in a sustainable, safe and cost-effective way, is a top priority. To fully understand the binder main properties and to decrease their CO_2 footprints, a sound description of their spatially resolved mineralogy is necessary. Developing this knowledge is very challenging as about half of the volume of hydrated cement is a nanocrystalline component, calcium silicate hydrate (C-S-H) gel. Furthermore, other poorly crystalline phases (e.g. iron siliceous hydrogarnet or silica oxide) coexist. Here, we have used ptychographic X-ray computed tomography (PXCT) for understanding the first days of cement hydration with the final goal to improve the mechanical strength performances of low-CO_2 cements. This work follows our previous investigation in PXCT of a cement paste at later hydration ages [1].

2. Materials and Methods

Three PXCT datasets for a Portland 52.5-type cement paste (nominal water-to-cement mass ratio=0.50) have been acquired at 19, 47 and 93 hours of hydration. Data were collected at the cSAXS beamline (SLS, PSI) in the same region of a ~0.2 mm diameter sealed glass capillary. The field of view was ~200 (width) and ~25 µm (height) and the voxel size was 187 nm. Each scan took about 4hours. The spatial resolution of the data was ~400 nm, measured by Fourier shell correlation and electron densities line profiles, see Figure 1.

3. Results and Conclusion

The submicrometer spatial resolution and accurate electron density have allowed to distinguish the different components with similar X-ray absorption and also showed precipitation and grains dissolving evolution. A machine learning image analysis approach, using the IPSDK software, permitted to segment the components with similar electron density, see Figure 1. This approach also permits to mitigate the influence of partial volume effects (around ~3pixels) in between labelled components for quantitative analysis. Details of the components evolution with hydration age will be reported and discussed.

4. Acknowledgements

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5. References

[1] Cuesta, A., et al. (2019).10.1107/S205225251900377

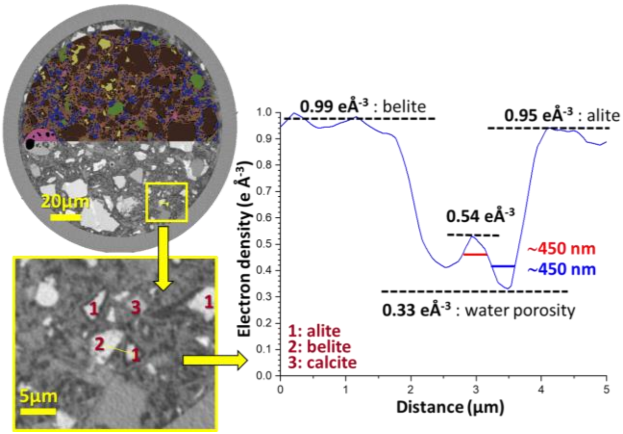

Figure 1. Machine learning volume segmentation overlaid on raw dataset at 19 h of hydration (top left). Color codes: air porosity (black), water porosity (blue), C-S-H and ettringite (light brown), portlandite (green), limestone (pink), alite and belite (dark brown), calcium aluminate ferrite (yellow). Anhydrous grains electron density and precipitation layer wall thickness line profile analysis (right).