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Towards High Fidelity Reconstruction of the Fabric of Naturally Deposited Sands using X-Ray Computed Tomography

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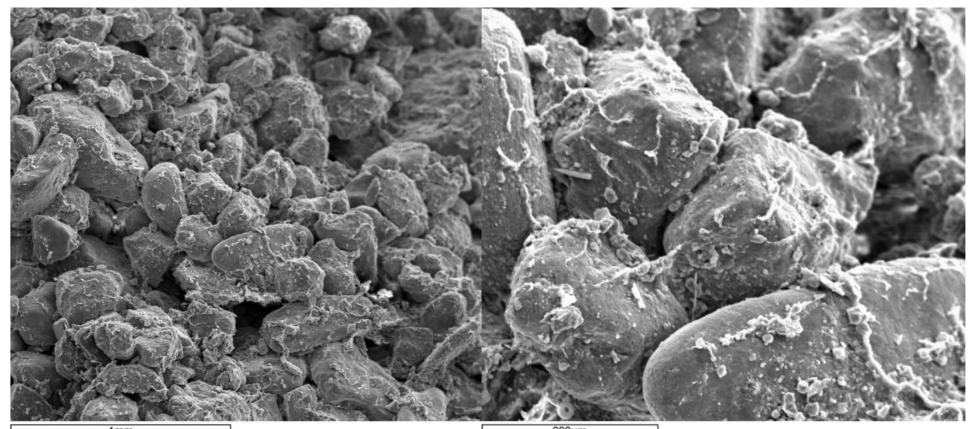
Motivation

Numerical modeling of the fabric of naturally deposited sands depends on being able to accurately reconstruct individual grains in a reasonable amount of time. To this end, X-Ray Computed Tomography (XRCT) is an excellent tool. However, while the currently available processing workflows, e.g. (Stamati, O., et al, 2020), have been successfully used to obtaining the shapes of clean, pluviated sands, the image reconstruction is a lot more challenging in resolving the individual grains and fabric of naturally deposited fine sands, such as shown in Figure 1. The focus of this study has been to develop a more robust that can rapidly reconstruct the grain avatars in sufficient detail.



0.1 mm) from a shoal in San Francisco Bay, Courtesy of ENGEO, Inc.

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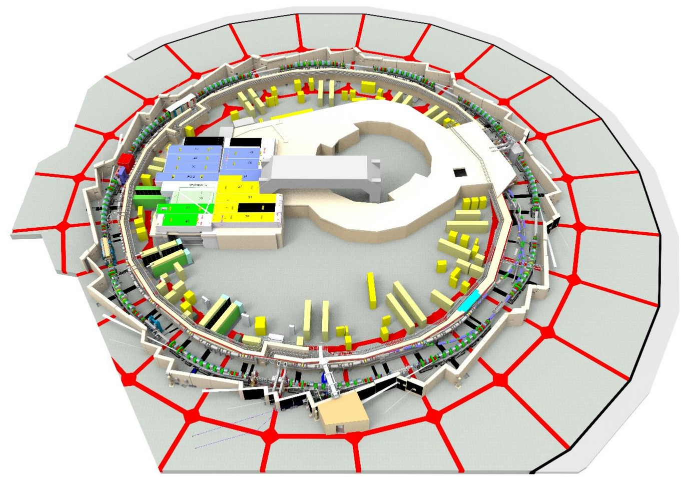


Beamline 8.3.2 – Hard X-ray Tomography

- 3rd generation synchrotron facility
- One of the brightest sources of soft x-rays
- Up to 48 KeV Energy
- 0.1 micrometer spatial resolution

Experimental Workflow

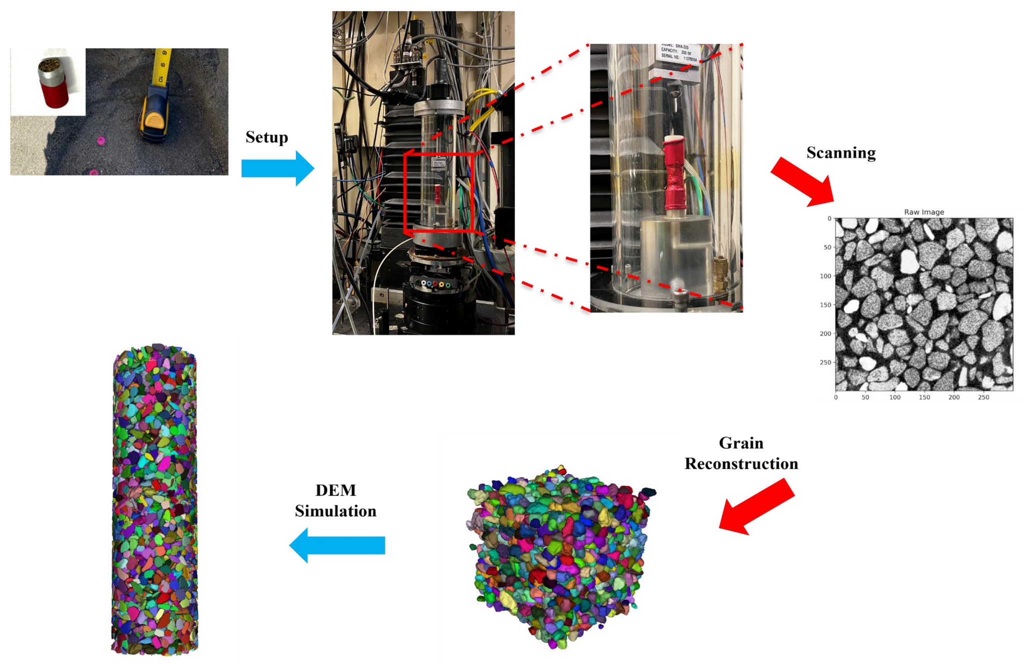
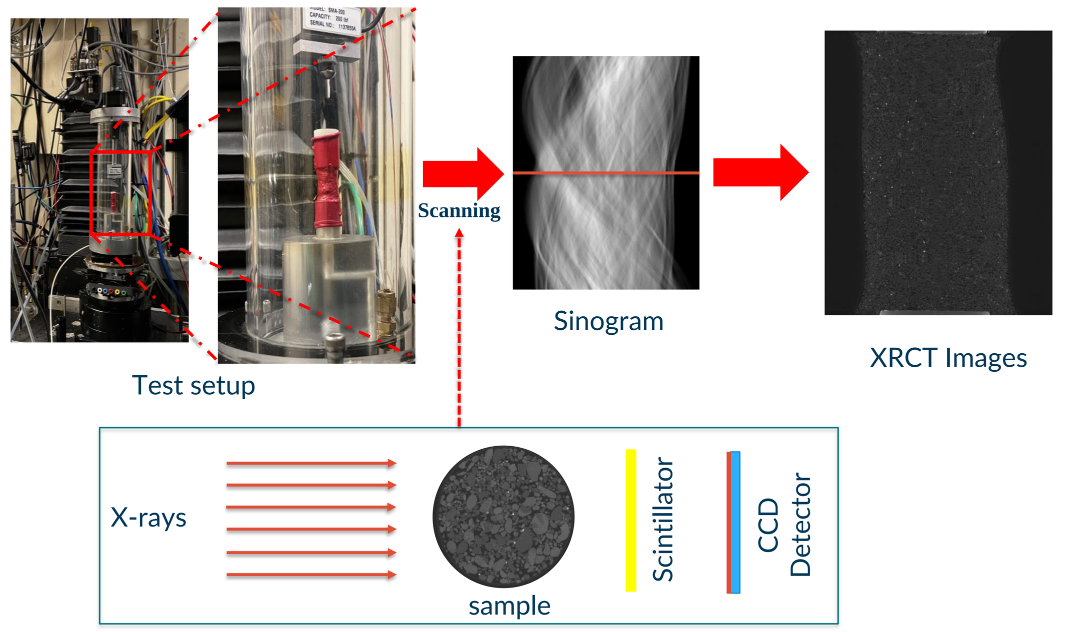


Figure 3: Steps of the workflow for sample reconstruction using XRCT

From Scanning to Avatars



- ❑ XRCT image reconstruction from sinogram
  - SVMBIR – Super Voxel Model Based Iterative Reconstruction
    Can be used on any dataset but high computational cost
  - MSD-Net – Mixed Scale Dense Network
    Can do the reconstruction with fewer X-ray projections but needs to be re-trained for new types of data.
- ❑ Image Segmentation
- ❑ Watershed Algorithm
- ❑ Level Set Reconstruction

XRCT Reconstruction with SVMBIR

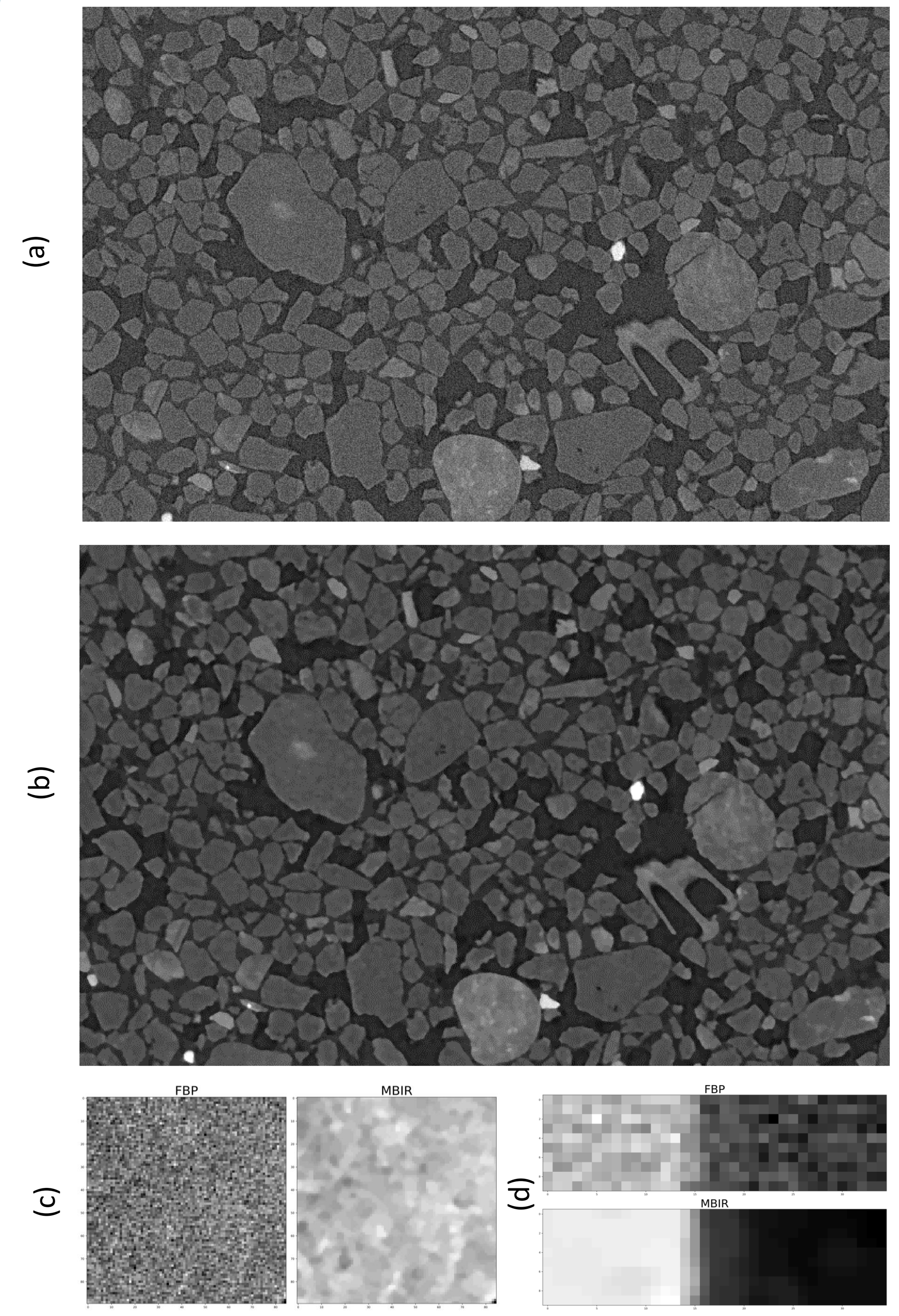
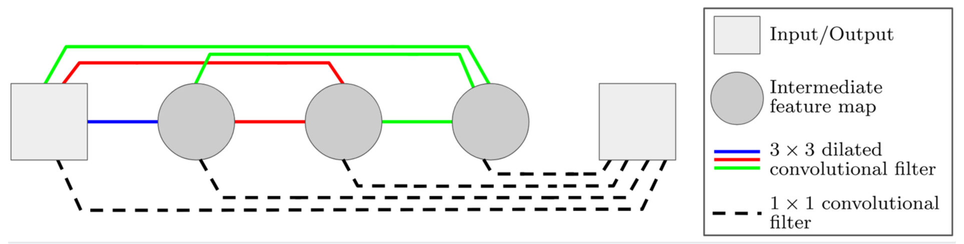


Figure 4: Visual comparison of FBP and SVMBIR reconstructions, (a) FBP reconstruction (b) SVMBIR reconstruction, (c) comparison of noise levels, (d) comparison of image gradient at boundaries

XRCT Reconstruction with MSD-Net



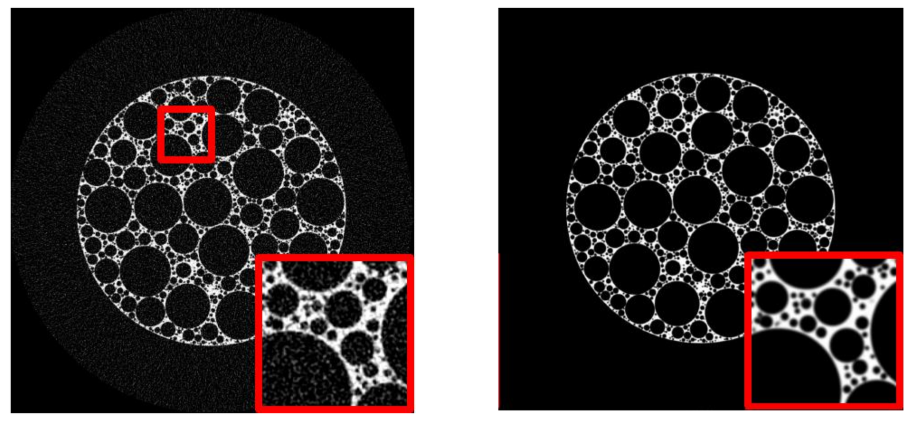


Figure 6: left – FBP reconstruction with 128 projections, right – MSD-Net reconstruction with 128 projections

Image Segmentation with U-Net

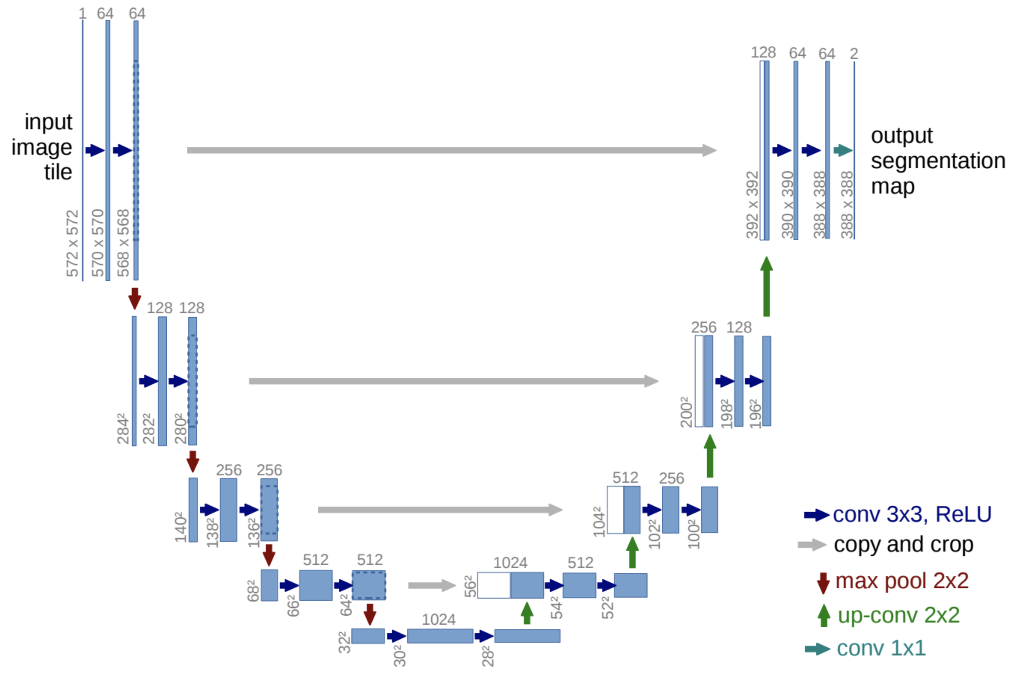


Figure 7: U-net Architecture, Ronneberger, et al (2015)

Image Segmentation Comparison

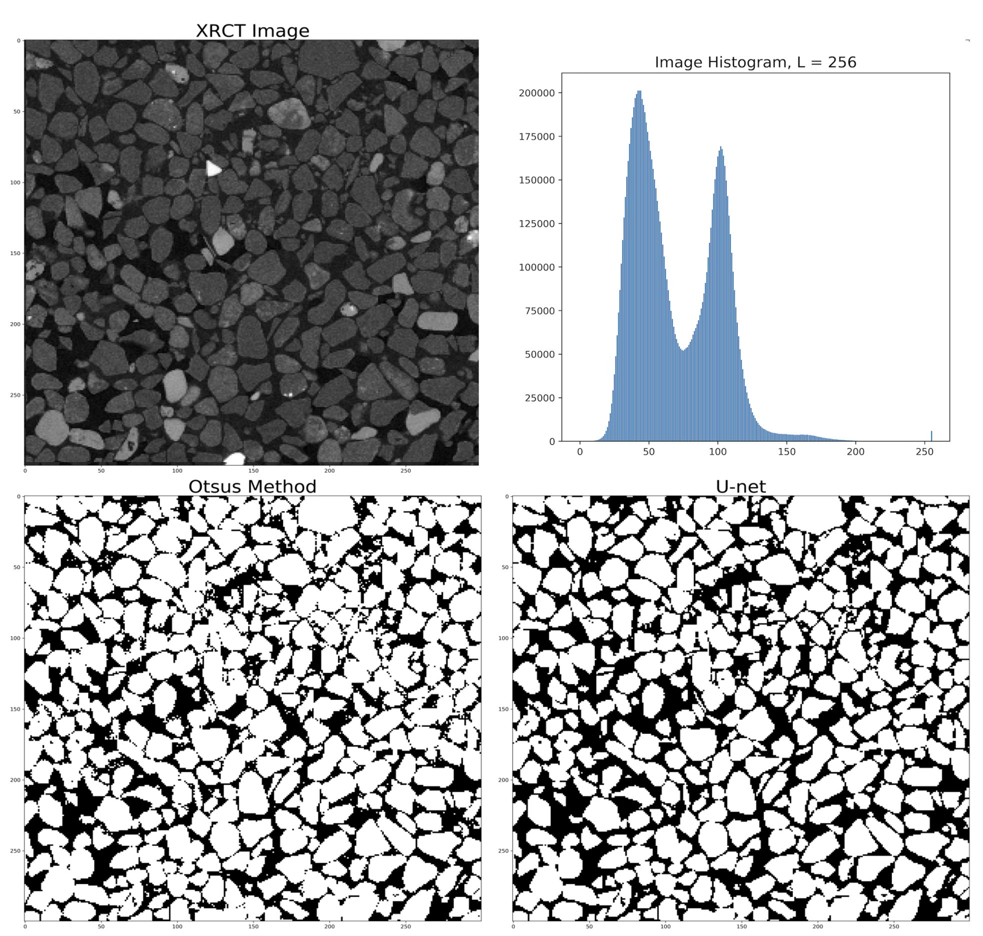


Figure 8: Comparison of Otsu's method and U-Net

Grain Reconstruction with Level Sets

We used DRLSE (Li et al(2010)) framework as an efficient and accurate approach identify the grain boundaries for the purpose of reconstruction. The following mean curvature flow penalty term was used to modify the DRLSE energy functional which then penalizes the large surface curvatures making the grains smooth, Figure 9.

$$\tau(\phi) = \frac{1}{2}\int_{\Omega} \kappa\|\nabla\phi\|\, d\Omega\,; \text{where } \kappa = \nabla\frac{\nabla\phi}{\|\nabla\phi\|}$$

Comparison of LS Reconstruction with Penalty

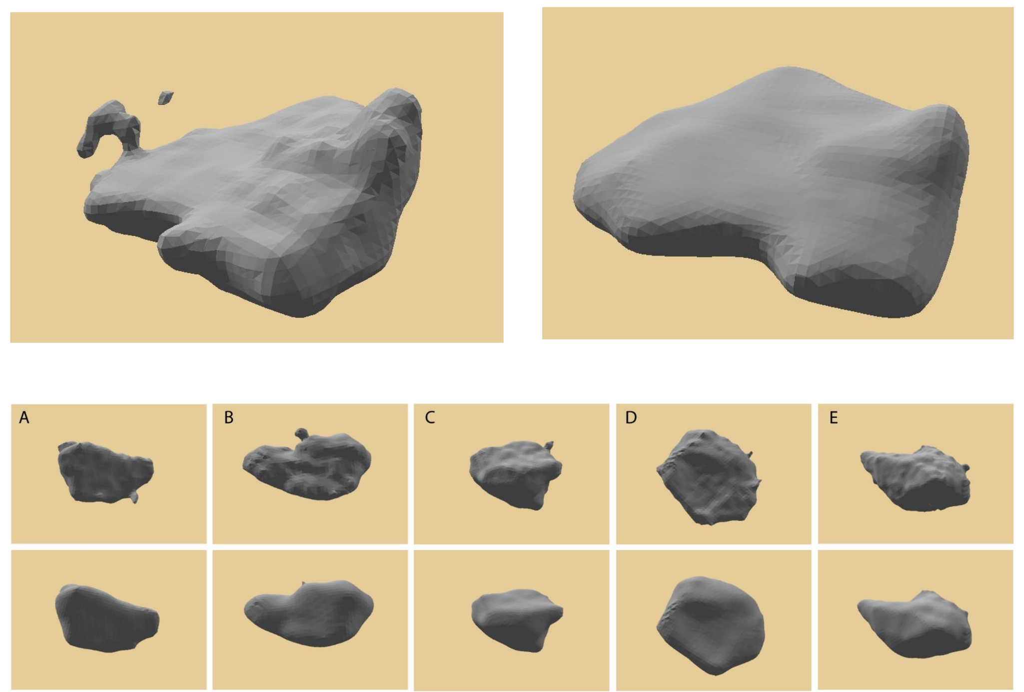


Figure 9: Comparison on the effect of introducing curvature smoothing penalty term, 0.01. Raw reconstructed shape in the top row and the smoothed shape of the same grain in the bottom row.

References

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