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Towards Real Time Segmentation of Large-Scale 4D Micro/Nanotomography Images in the Sirius Synchrotron Light Source

Thiago V. Spina,[1] Gustavo J. Q. Vasconcelos,[1,2] Henrique M. Gonçalves,[1,2] Gustavo C. Libel,[3] Helio Pedrini,[2] Tiago J. Carvalho,[4] and Nathaly L. Archilha[1]

[1.] Brazilian Synchrotron Light Laboratory (LNLS), Brazilian Center for Research in Energy and Materials (CNPEM), Campinas, Brazil.
[2.] Institute of Computing, University of Campinas, Campinas, Brazil.
[3.] Department of Informatics, Federal University of Technology – Paraná, Curitiba, Brazil.
[4.] Federal Institute of Education, Science and Technology of São Paulo – Campinas, Campinas, Brazil.
* Corresponding author, thiago.spina@lnls.br.

The Brazilian Synchrotron Light Laboratory (LNLS) is currently engaged in the development and construction of Sirius, a fourth generation Synchrotron Light Source. Its ultra-low emittance (0.28 *nm*.rad) and high brightness will allow the execution of very competitive experiments, opening new perspectives for research in fields such as oil and soil science, and structural biology. The proposed X-ray tomography beamline at Sirius, named MOGNO (MicrO and NanO Tomography), is being designed to be a micro and nano imaging beamline focused towards multi-scale analysis of the internal 3D structures of different materials and objects, and also, due to its high flux, time-resolved experiments (4D tomography) will be available in both low and high energies (27/67.5keV). 4D tomography contains a series of 3D images with roughly 3.6 gigavoxels (up to 14 GB) each, which will be obtained in the order of 1-5s [1]. Hence, MOGNO may generate *Terabytes* of 4D data in a few minutes. This is orders of magnitude more than the current microtomography imaging beamline (IMX) at LNLS, in which a single 3D image acquisition may take from 15 minutes (e.g., biological materials) to 4 hours (e.g., rocks).

We aim to maximize the throughput of the MOGNO beamline usage by allowing researchers to leave Sirius with as much processed data as possible about their scientific case. In this paper, we present an overview of the strategies we have been taking towards addressing the real time image segmentation needs of MOGNO. This is a major challenge given the broad scope of samples that can be analyzed using X-ray microscopy. We have been using High Performance Computing techniques and Machine Learning to speed up traditional image segmentation methods and also to develop novel methods.

Our first major contribution is a parallel GPU version of the *watershed transform*. The watershed transform is a very popular seed-based image segmentation method via region growing. The Image Foresting Transform [2] (IFT) provides a CPU implementation of the watershed transform based on optimum seed competition. We have implemented a parallel version of the IFT competition and tested it to generate superpixels as in [3]. We have achieved speedups ranging from 65 to 105 times, not including memory transfer, for 2D slices with size of 2048x2048 pixels of a 3D image of carbonate rock sample imaged using the IMX beamline (Fig. 1), segmenting each slice in 0.02s-0.036s.

A key issue with watershed-based segmentation is how to place the seeds in critical locations of the image for properly delineating the objects of interest. Even if we have a very efficient watershed

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algorithm, improper automatic seed selection will demand user intervention to fix mistakes in delineation. We propose to use Machine Learning to tackle this issue in two ways. First, we compute a superpixel classification system that classifies 2D slices of the 3D image, to determine which superpixels should be selected as foreground or as background seeds for watershed segmentation. Superpixels reduce the time for training and classification, and may improve the segmentation result by providing local contextual information about the voxel intensities of the objects of interest. We have trained our method to classify superpixels as belonging to either rock grains or pore space, aiming to segment pore networks of carbonate rock samples. We have assessed multiple strategies to extract features that represent the superpixels and classification methods, aiming to determine the most robust combination that can be implemented in parallel on GPU in the future. Our studies pointed out that some features extracted using pixel neighborhood-based filters from Scikit-image (a Python image processing library) and the Random Forest classifier yielded the best accuracy (91% of Dice similarity).

Our second approach was to evaluate U-net [4], a popular *Deep Learning* convolutional neural network model. U-net provides a classification probability of a pixel to belong to one out of two objects of interest. We then select seeds via threshold and produce a final segmentation using watershed (Fig. 2). We have trained and evaluated the model using the same images as for the superpixel classification task, and achieved 89% of Dice similarity. This is an interesting result when comparing with our superpixel-based method, since normally Deep Learning has demonstrated to achieve superior results. We have trained and tested both models with two fully annotated patches containing 20 and 35 2D slices of sizes 137x127 and 116x106 pixels, respectively, extracted from the core region of two 3D images. We believe that this amount of data is insufficient to robustly train the U-net, even though we performed data augmentation. Notwithstanding, superpixel-based classification seems to be a prominent strategy to achieve real-time image segmentation with high accuracy. We believe that the strategies we have been adopting are an interesting first step towards real-time image segmentation. Moreover, they might serve other researchers who rely on X-ray microscopy image analysis as well. In the future, we aim to test both methods after acquiring more annotated data and heavily parallelize the developed algorithms [5].

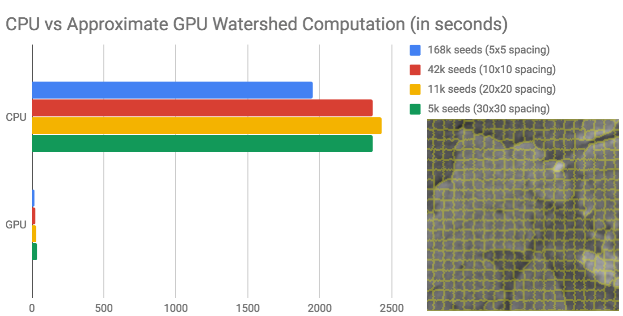

Figure 1: Performance comparison for different number of seeds for superpixel generation (right).

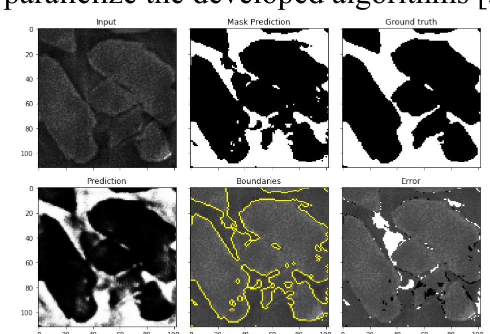

Figure 2 : U-net based probability prediction, and watershed segmentation from the generated seeds.

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