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3D Platform for Machine Learning Based Segmentation and Visualization Using FIB-SEM Imagery

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In this work, we are demonstrating a 3D platform focused on segmentation and interactive visualization of large FIB-SEM (Focused Ion Beam Scanning Electron Microscopy) volume data out-of-core. The segmentation technique uses a random forests based classifier with a set of 25 features. We have picked a publicly available dataset [1] to showcase our platform that can help image analysis, machine learning and domain experts write and integrate custom algorithms for large 3D volumes. Large data analysis in EM imagery requires domain experts validating or providing ground truth data which is primarily a manual and laborious task. For image analysis experts, a platform for accessing data out-of-core, training a classifier, computing features, visualizing partial or final results in 3D can be beneficial for setting up large scale experiments. Such a workflow requires a programming platform that is capable of handling data out-of-core and be extensible. Giving researchers access to a complete end to end platform that is customizable and extensible, from analysis to visualization of large 3D can be a powerful tool focused on an image analysis expert centric workflow.

Image stacks produced by FIB-SEM can be at nanometer resolution and help with understanding intricate structures. As opined in [2] due to the laborious nature of annotating large 3D image stacks, the data goes unused and hence not analyzed. The dataset is a 5x5x5 micrometer sized section of taken from a CA1 hippocampus region of a mouse brain corresponding to two ground truth volumes, one for testing and another for training segmentation algorithms. The size of one voxel in the full dataset is 5x5x5 nanometers.

Many automatic algorithms for segmentation have been proposed [3,4] for specifically segmentation of mitochondria in this FIB-SEM stack. Our random forests based machine learning classifier is built by training a set of 25 randomly generated filters that help discriminate between foreground and background, which in this segmentation is mitochondria versus non-mitochondria regions. The randomly generated filters are stored in a custom file format as a 3D volume that can be retrieved during the testing or prediction step. Our randomly generated filter bank comprise of a representation of powerful discriminative features that can help distinguish between the mitochondria and non-mitochondrial regions. Handpicked feature sets versus convolutional neural network (CNN) based auto weighted features, both have their advantages and disadvantages. Handpicked feature sets require image processing or computer vision based knowledge about discriminative features while understanding the convolutional neural network's learned feature set can be challenging. Our approach of using a set of randomly initialized filters shows that progressively learning the structures of interest can be achieved quickly and efficiently and help tune the inputs. Our goal with the feature set is to show a generic filter bank and its impact on how a classifier can learn.

We have implemented our entire EM learning, classification using a modern version of the Open Inventor toolkit. [5,6]. Open Inventor is a visualization and processing application programming interface that makes it easy for programmers to visualize and process large 3D data while exposing a simpler interface. Open Inventor makes OpenGL calls to perform the rendering while using a computational framework for image processing. The random forests algorithm implementation uses a modified version of the original code from [7].

The experiments include generating a filter bank of 25 randomly initialized features followed by convolution of each of these filters with every slice of the training volume provided [1]. A random forests based classifier is then trained with this set of computed features and the known labels for each voxel (0-for background/non-mitochondrial voxel or 1-for foreground/mitochondrial voxel) from the ground truth volume. The feature filters are stored as a 3D volume comprising of 25 z-slices along with a trained classifier. The testing platform then loads the 3D grayscale stack and the filter volume. Convolutions are performed slice by slice on grayscale image stack using each of the 25 filters. The classifier then predicts a label for each voxel along with a probability or confidence value. Our platform can also visualize the results of the classifier progressively as it is being trained in order to visually check the effects of supplying more or less ground truth voxel and feature data. All of our image processing, training and classification is multi-threaded code that only loads one slice in main memory in order to be able to run on laptops with less compute power. The visualization of large volumes is also optimized to run on memory starved graphics hardware such as on laptops.

The final results can be visualized using interactive volume rendering of grayscale data along with classified voxels as detected mitochondrial structures as foreground. Users can slice through the data interactively while observing the predicted structures. The computation and visualization framework utilizes least amount of main memory possible while retaining the interactivity and ease of interpretation of the results using the out-of-core visualization principles.

We have introduced a flexible, extensible and powerful platform for processing and visualization of large 3D volumes. Our random forests based machine learning integrates within the processing platform to train on progressively out-of-core large 3D data.

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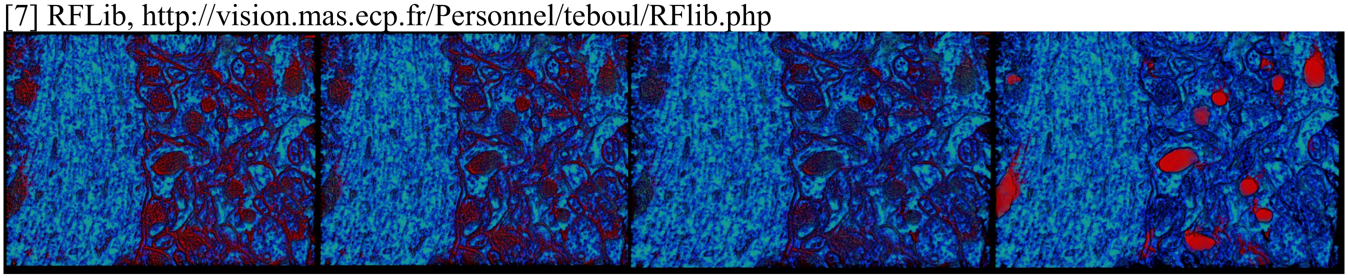

Figure 1. (L-R) (a) FIB-SEM Volume with classifier predicted foreground labels shown in dark red. (b) Classifier prediction of foreground after training on 10 slices (c) Classifier prediction after training on all slices. (d) Ground truth shown in bright red