Neural Processes Segmentation in Confocal Microscopy Datasets using the GPU

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Introduction

Background – Although the microscopic physiology of individual neurons is well understood, scientists still lack a macroscopic understanding of how the brain works. One solution to this problem is a bottom-up approach: find out how individual neurons are connected and use the information to understand the complexity of the brain.

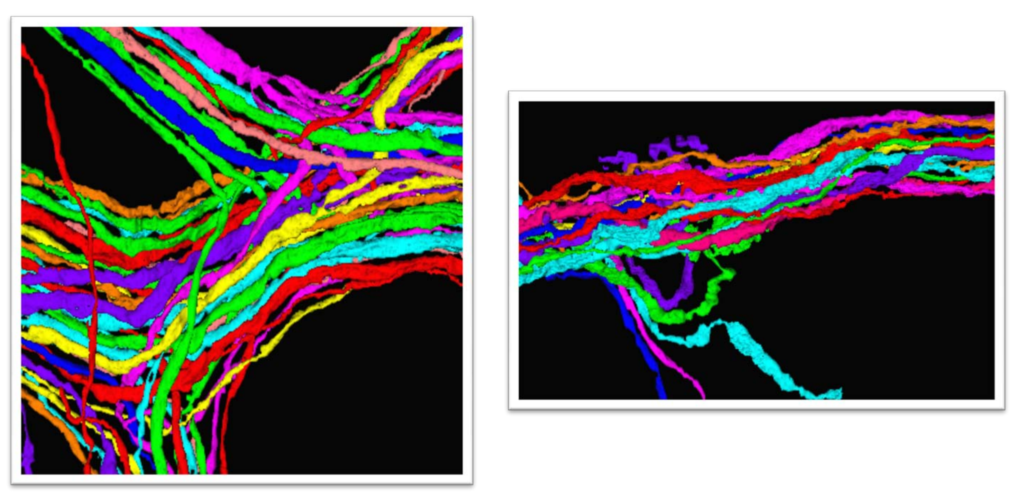

Figure 1: Hand segmentation data from a neuroscientist [4]. Each axon is individually labeled with a different color.

Purpose -The purpose of the Connectome project is to semi-automatically map the neurons of the human brain. We are facing a daunting task; the one hundred billion neurons of the human brain mean terabytes of data that make manual segmentation infeasible. In order to expedite this process and provide an interactive interface, the algorithms are implemented on the GPU due to its substantial advantage in parallel computation.

Methods – We segmented axons in the confocal microscope images from the Interscutularis muscle of adult transgenic mice. The segmentation algorithms tested are the level set and the shortest path method.

Level Set Method

We treat neural processes as a topologically tubular object. The main idea is applying 2D level set segmentation to each cross section of the 3D neural process. The entire 3D surface can be reconstructed by stacking up the 2D curves.

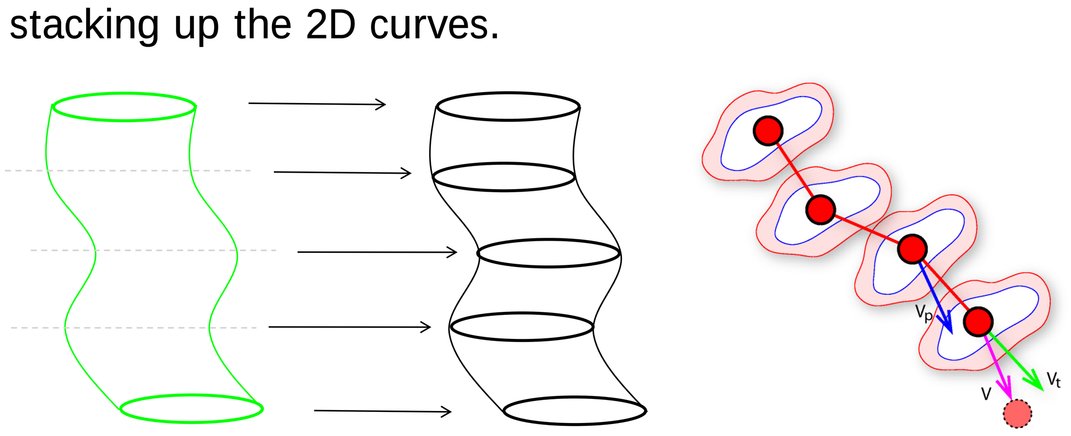

Figure 2: Our 3D tracking / segmentation method using 2D segmentation results.

For 2D segmentation, we use a level set method, a surface growing and shrinking algorithm to move an initialized boundary. The area grows inside the axon, and shrinks outside of it, converging at the axon boundary.

$$\frac{d\phi}{dt} + (\alpha \mathbf{F}_D + \beta \mathbf{F}_K)|\nabla \phi| = 0$$

The algorithm is dependent on the following parameters:

1. **Intensity (F_D)** - Converges at a specified intensity.
2. **Curvature (F_K)** - Prefers round shape over odd contortions.

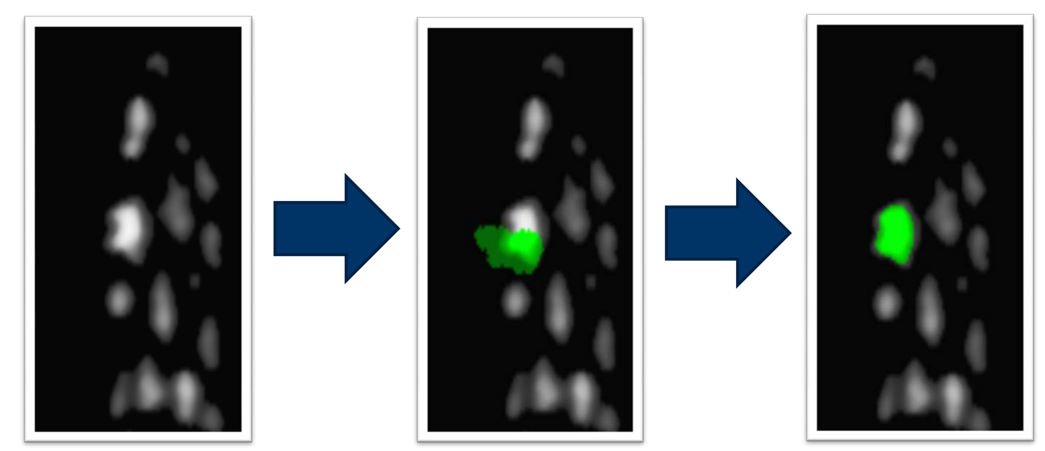

Figure 3: The image shows the steps through which the level set works on a 2D slice. The original image (left) is first initialized with a fluorescent green area (center) and then the level set algorithm automatically moves the green initialization to the boundaries (right).

Results

We propagate 2D level sets onto the next slice by using the previous level sets as an estimate for the location of the next. Each slice is fitted with an ellipse to find the center of the axon.

Advantages

1. Interactive - allows for corrections on the fly.
2. Able to trace center of the axon.

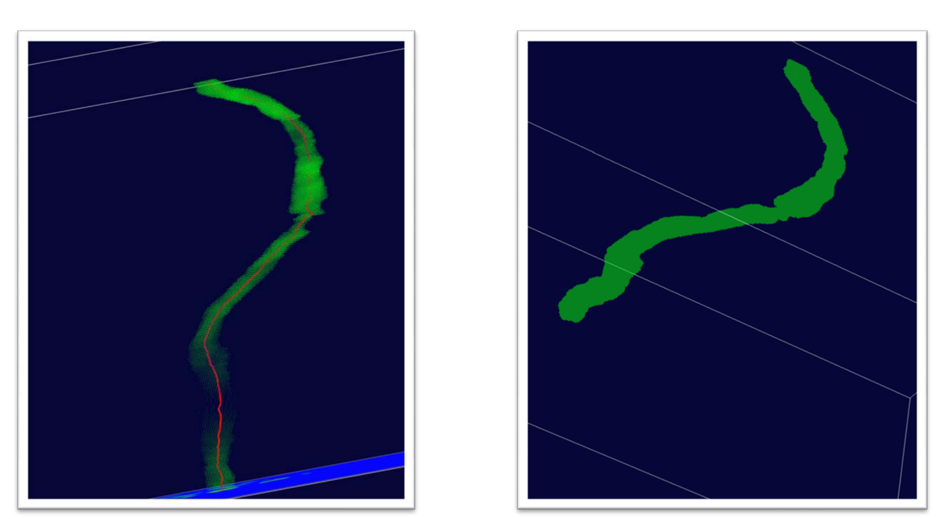

Figure 4: Results of level set segmentation, the axon is colored in fluorescent green with the center labeled with red dots.

Shortest Path Method

The main idea behind the shortest path method is that any neural connection can be decomposed into a set of simple connections between two end points. The shortest path between two points can be found by solving the Eikonal equation twice using each endpoint as a seed point [2].

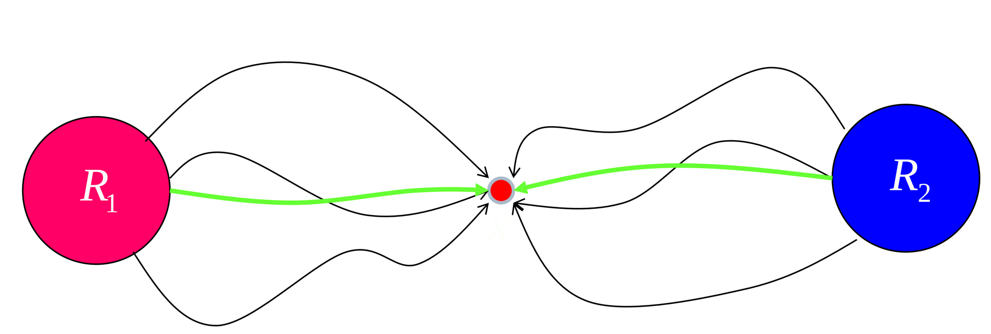

Figure 5: Although there are multiple paths to any pixel x (black lines), there exists one path (green) that is the shortest path between the two seed points (R_1 and R_2) and to that given pixel.

The solution of the Eikonal equation (shown below) creates a distance map from initial seed points.

$$|\nabla \phi|^2 = \frac{1}{F^2}$$

We assign a speed value F per each pixel based on the image intensity in order to propagate faster inside the axons.

To handle multiple seed points, we extend two-way propagation [2] to n-way propagation as follows:

- Find all possible end points by extracting local maximum points on all six sides of the input volume.
- Solve the Eikonal equation once for each end point.
- Among n distance values, pick the smallest two.
- Backtrace to the corresponding end points.

Results

By doing this, we can segment multiple axons simultaneously without manually pick two end points as in [2]. Each shortest path corresponds to a unique axon.

Advantages

1. Faster than 2D level set method.
2. Robust with low intensity axons.

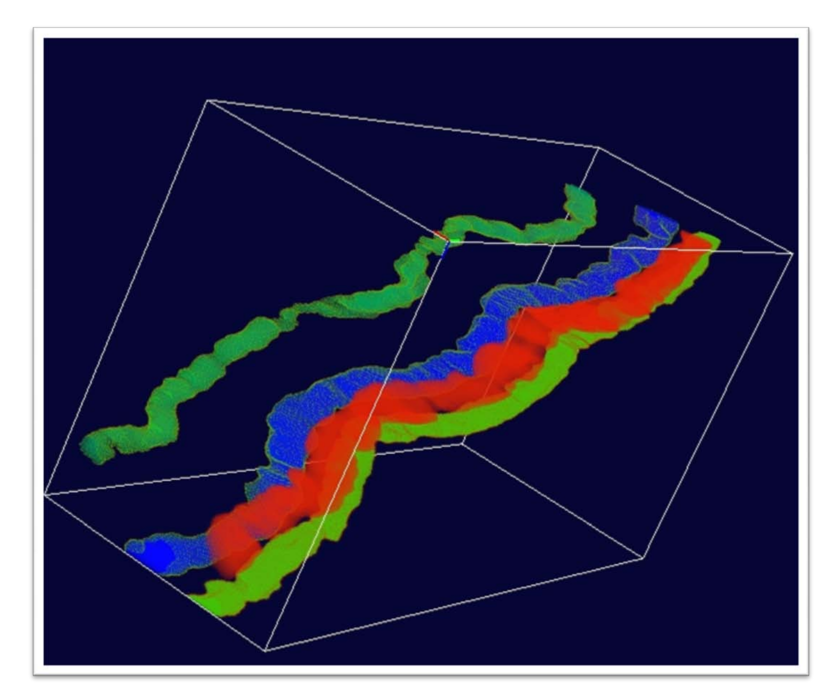

Figure 6: Results of the shortest path segmentation method. Each individual axon is labeled with a different color.

GPU Implementation

Efficient implementation of the GPU level set and Eikonal solver requires the adaptive update scheme that updates only in the currently active region. To implement those methods on the GPU, we employ a block-based update scheme originally proposed by Lefohn et al. [3].

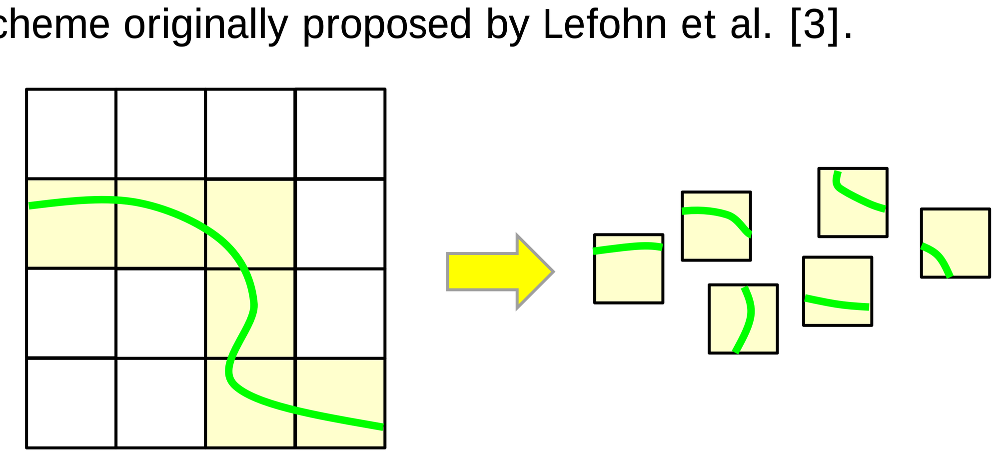

Figure 7: Image showing the blocks passed off to the GPU rather than individual boundary pixels passed to the CPU.

We use the FIM [1] to solve the Eikonal equation on the GPU. The method does not use an expensive sorted data structure, e.g., Heap, but each active block is repeatedly updated until it converges. A converged block can be re-activated later if any update of one of its neighbor block affects it. The algorithm runs until no more active block is left.

GPU v.s. CPU Performance Comparison

Our GPU level set solver runs about **24** times faster than CPU implementation using the ITK library. Our GPU FIM runs up to **120** times faster than the ITK fast marching implementation [1].

Conclusion

Summary

We have demonstrated the capability to segment axons from confocal microscopy data using both the level set and shortest path method, bringing us one step closer to being able to understand how the brain functions. The use of the GPU resulted in a significant speed up compared to CPU-based methods, allowing the level set method achieve interactive speeds and substantially reduce the time to compute distance maps by solving the Eikonal equation.

The current method has problems on particularly tough datasets due to the following reasons:

1. Attenuation issues with confocal microscopy – some axons are substantially brighter than others.
2. The fluorescent proteins' inability to penetrate the mitochondria – the axons can disappear for slices, breaking the level set.

Future Work

1. Employing directionality (anisotropy) into the distance computation in order to apply strong weights along the axon direction.
2. Robust automated seed point detection.

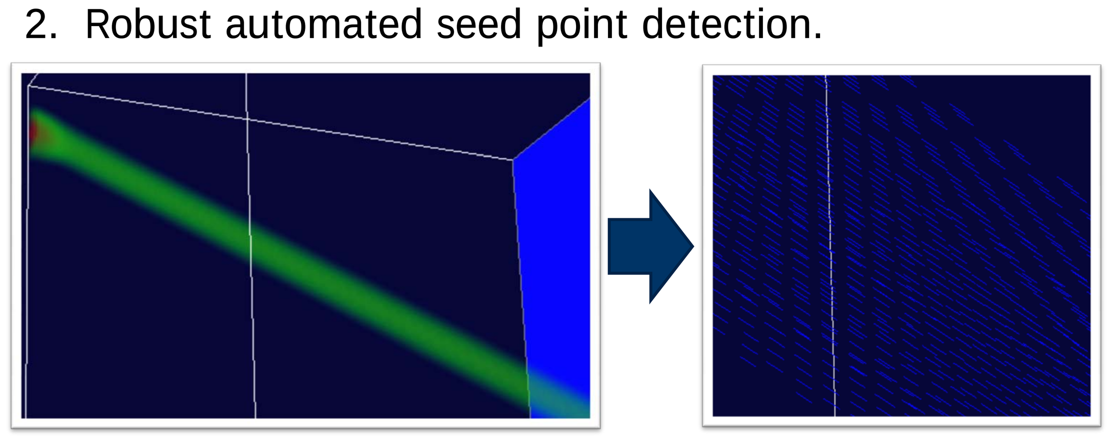

Figure 8: Axon test image showing the original image (left) and the correctly aligned blue tensors (right) in the direction of the axon for anisotropic Eikonal equation.

References

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