Neural Process Reconstruction from Sparse User Scribbles

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Introduction

Mapping neural circuitry is an important ongoing challenge in neurobiology. Current approaches to this task involve tracing neural processes through segmented nanometer-scale EM (electron microscopy) image stacks of brain tissue. Since our understanding of neural circuitry is often limited by our ability to reconstruct neural processes from EM image stacks, accurately segmenting neural processes is an important open problem in the medical image analysis community.

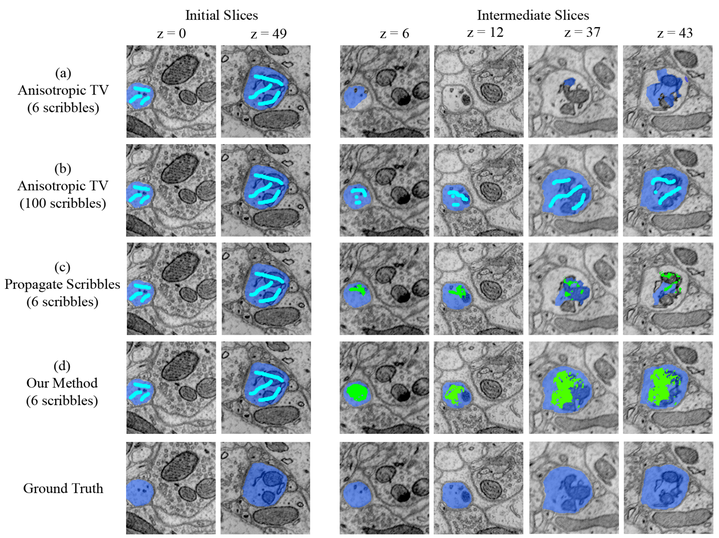
Dense neural reconstruction algorithms (Jain et al. 2010; Kaynig et al. 2010a; Kaynig et al. 2010b; Lucchi et al. 2010; Mishchenko 2010; Venkataraju et al. 2009; Andres et al. 2008) generally rely on supervised learning methods to automatically classify every pixel in electron microscopy image stacks according to the type of cellular structure to which it belongs. However, in practice, these methods can require significant user effort to correct errors in the automatically generated segmentations.

Sparse neural reconstruction algorithms (Chklovskii et al. 2010; Jeong et al. 2009; Pan et al. 2009; Vazquez-Reina et al. 2009; Jurrus et al. 2008; Macke et al. 2008) rely on the user to interactively guide the segmentation of individual neural processes. Most existing sparse algorithms compute 3D reconstructions as sequences of locally optimal 2D segmentations. However, these methods do not optimally enforce 3D geometric consistency constraints on the resulting 3D segmentation, and can require significant user effort to adjust the resulting segmentation.

In this poster, we introduce a novel semi-automatic method for neural process reconstruction that only requires very sparse scribble annotations as input. We evaluate our method by reconstructing 16 neural processes in a 1024x1024x50 nanometer-scale EM image stack of a mouse hippocampus.

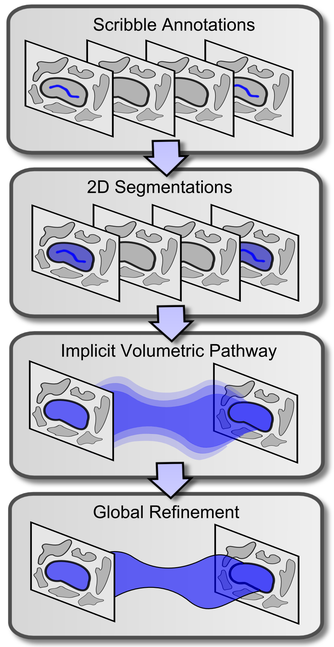
We demonstrate that, on average, our method is 68% more accurate than Markov Surfaces (Pan et al. 2009), 91% more accurate than Geo-Cuts (Boykov and Funka-Lea 2006), and 263% more accurate than Marker-Controlled Watersheds (Gonzalez 2006).

Key Motivating Observations



Anisotropic Total Variation (Unger et al. 2009) fails to segment this neural process from very sparse scribble annotations (a), but succeeds if scribble annotations are given on every slice (b). Our method only requires scribble annotations on the first and last slices because we automatically propagate segmentation constraints through the image stack. However, propagating scribbles as segmentation constraints results in a significant under-segmentation of this neural process (c). Instead, we propagate 2D segmentations, resulting in an accurate segmentation of this neural process (d). Scribble annotations are shown in light blue, segmentations are shown in dark blue, and automatically propagated segmentation constraints are shown in green.

Overview of Our Method



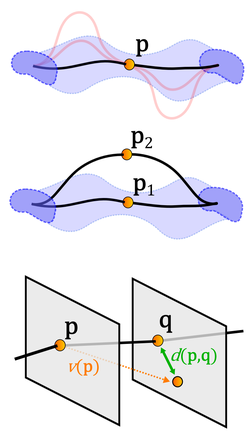
We assume that we are given scribble annotations indicating a neural process of interest on the first and last slices of an image stack.

We compute 2D segmentations that contain the scribble annotations and align with strong image edges; these 2D segmentations define hard constraints on our 3D segmentation.

We propagate the 2D segmentations through the image stack according to an implicitly represented volumetric pathway, which we compute based on the dense optical flow between image slices; the interior level sets of this volumetric pathway define soft constraints on our 3D segmentation.

We compute the final 3D segmentation by globally refining the volumetric pathway according to an anisotropic variational segmentation model that aligns with strong in-plane image edges and enforces 3D smoothness.

Computing a Volumetric Pathway

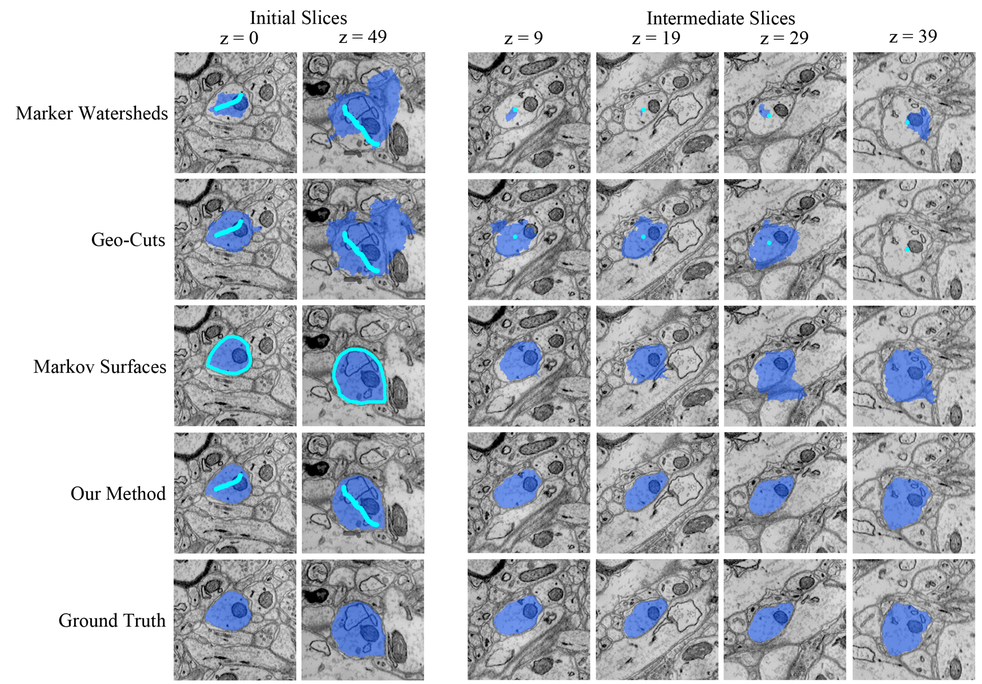


There are many possible paths through the image stack (shown in red) that connect the 2D segmentations on the first and last slices (shown in dark blue) via **p**, *but there is only one shortest path (shown in black); we set the cost of each pixel in a cost volume to be the length of this path.*

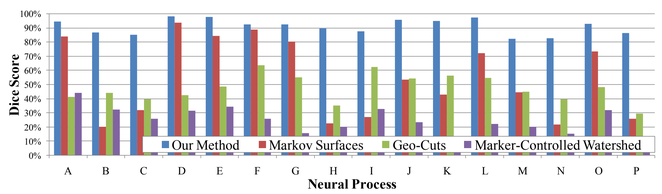
For example, $\mathbf{p}_2$ *will be assigned a higher cost than* $\mathbf{p}_1$ *since the length of its shortest path is longer; this means* $\mathbf{p}_2$ *is less likely to belong to the neural process of interest than* $\mathbf{p}_1$.

When computing the length of each path, we model the distance between pixels **p** *and* **q** *on adjacent slices (shown in green) as a function of the optical flow vector originating at* **p** *(shown in orange). In this formulation, paths through the image stack that agree strongly with the optical flow field will have very short lengths, and the pixels belonging to these paths will be assigned very low costs. Thus, the volumetric pathway will contain pixels that are likely to belong to the neural process of interest.*

Results



Segmentation results from our method, Markov Surfaces (Pan et al. 2009), Geo-Cuts (Boykov and Funka-Lea 2006), and Marker-Controlled Watersheds (Gonzalez 2006) on various slices of a 1024x1024x50 mouse hippocampus EM image stack. Bright blue regions indicate user-provided annotations used to initialize the algorithm, dark blue regions indicate the resulting segmentations.



Accuracy of our method, Markov Surfaces (Pan et al. 2009), Geo-Cuts (Boykov and Funka-Lea 2006), and Marker-Controlled Watersheds (Gonzalez 2006) while segmenting 16 neural processes in an annotated 1024x1024x50 mouse hippocampus EM image stack. On average, our method is 68% more accurate than its closest competitor.

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