EXTREME IMAGE SEGMENTATION

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1. Motivation

Image decomposition is the task of deciding, for every pair of points in an image, whether those points belong to the same or distinct structures. For instance, decomposing a three-dimensional microscopy image into biologically meaningful structures is fundamental to biomedical image analysis. Abstractions of this task in the form of mathematical optimization problems and algorithms for solving these problems typically have parameters for balancing two classes of errors: false joins and false cuts. Only rarely, however, are image decomposition algorithms assessed simultaneously in settings where the risk of false joins and false cuts is extreme. Yet, such analyses are desirable for tasks where extreme risks of false joins and false cuts occur simultaneously, in different parts of the same image, e.g. in the field of Connectomics. The goal of this project is to facilitate such analyses.

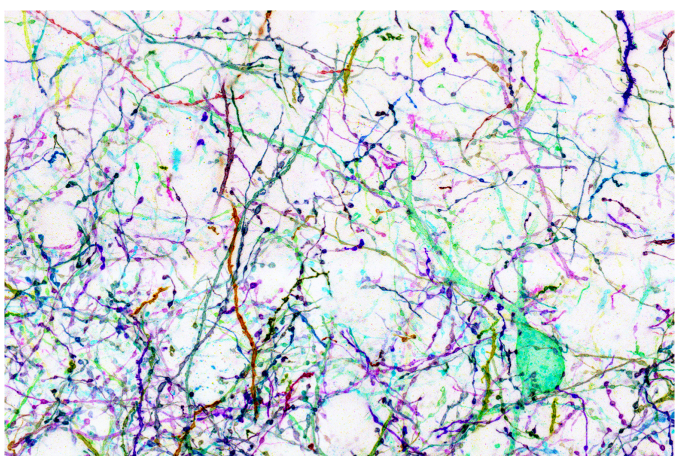

Figure 1. Decomposing a volume image that contains thin tubular structures such as the neuronal processes depicted in the slice from [1] above is challenging due to a high risk of false cuts.

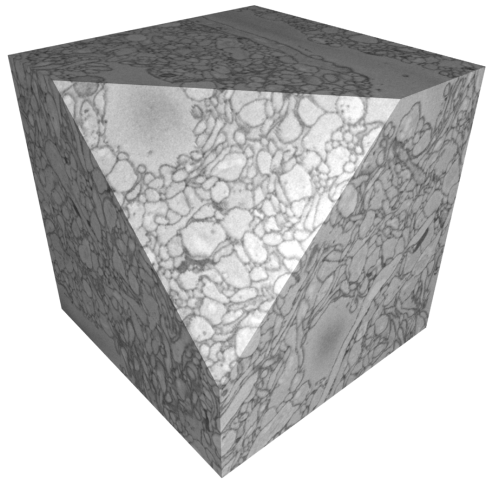

FIGURE 2. Decomposing a volume image into objects separated only by thin membranes, such as the neurons in the image from [2] above, is challenging due to a high risk of false joins.

2. TASKS

In order to analyze image decomposition algorithms in settings where the risk of false joins and false cuts is extreme, the first task of this project is to construct algorithmically two problem sets of synthetic image segmentation tasks for which the risk of false joins and false cuts is different and extreme. The second task is to implement an image decomposition algorithm for solving these problems. The third task is to compare the decompositions obtained by this algorithm to the known truth in terms of two well-known and widely-used metrics.

2.1. **Construction of problem sets.**

(1) Define a set of synthetic image decomposition tasks similar to the natural one shown in Fig. 1. Therefor:
   (a) Write a program that outputs $m \in \mathbb{N}$ random smooth curves that intersect the unit cube $[0, 1]^3$ and never get closer to each other than a parameter $d > 0$. Hints:
      - Consider using splines
      - Consider choosing curves at random and rejecting ones that get too close to any other curve
   (b) Write a program that takes this set of curves as the input and outputs a noisy 8-bit digital volume image of n^3 pixels showing these curves. Pixels far from all curves shall have a gray value near 0 with high probability. Pixels near any curve shall have a gray value near 255 with high probability.

(2) Define a set of synthetic image decomposition tasks similar to the natural one shown in Fig. 2. Therefor:
   (a) Write a program that outputs a random tessellation of the unit cube $[0, 1]^3$ into $m \in \mathbb{N}$ random sub-volumes. Do it in such a way that the sub-volumes are not necessarily convex. Hints:

- Consider starting with a Voronoi tessellation
- Consider starting with $n \gg m$ Voronoi cells and merging random pairs of neighboring cells until you have m cells left.
- Consider using a library for 3D Voronoi tessellations.

(b) Write a program that takes this tessellation as the input and outputs a noisy 8-bit digital volume image of n^3 pixels showing this tessellation. Pixels far from all boundaries between cells shall have a gray value near 0 with high probability. Pixels near any boundary shall have a gray value near 255 with high probability.

2.2. **Implementation of an image decomposition algorithm.**

(1) Implement an algorithm of your choice for tackling the problem sets you defined.
   (a) If you wish to keep it simple, consider a classical algorithm such as watershed segmentation
   (b) If you wish to obtain state-of-the-art results and potentially contribute to original research, consider the problem statement and local search algorithms of [3].

2.3. **Empirical analysis.** For any pair of points in the image it is known from the construction of the problem whether those belong to the same or distinct structures. Hence, the next task is to compare the decompositions of the image obtained by the algorithm from the previous task to the known truth.

(1) Compare the decompositions by computing Rand's index
(2) Compare the decompositions by computing the variation of information

References

[1] https://news.engin.umich.edu/2017/08/7-75m-for-mapping-circuits-in-the-brain.
[2] Bjoern Andres, Ullrich Köthe, Thorben Kröger, Moritz Helmstaedter, Kevin L. Briggman, Winfried Denk, and Fred A. Hamprecht. 3D Segmentation of SBFSEM Images of Neuropil by a Graphical Model over Supervoxel Boundaries. *Medical Image Analysis*, 16(4):796–805, 2012.
[3] Evgeny Levinkov, Jonas Uhrig, Siyu Tang, Mohamed Omran, Eldar Insafutdinov, Alexander Kirillov, Carsten Rother, Thomas Brox, Bernt Schiele, and Bjoern Andres. Joint graph decomposition and node labeling: Problem, algorithms, applications. In *CVPR*, 2017.