Image segmentation

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

A key bottleneck in the efficient and timely presentation of three-dimensional data sets eg for clinical purposes is their volumetric segmentation.

In neurosurgery, there is a long history of applying segmentation tools, and in particular volumetric methods, to the evaluation of patients with hydrocephalus and candidates for epilepsy surgery.

see Tumor segmentation.

see Automated segmentation.

see Manual segmentation.

A physics-based medical image segmentation method is developed. Specifically, the image greyscale intensity is used to infer the voxel partial volumes and subsequently formulate a porous medium analogy. The method involves first translating the medical image volumetric data into a three-dimensional computational domain of a porous material. A velocity field is then obtained from numerical simulations of incompressible fluid flow in the porous material, and finally, a velocity iso-surface provides the surface description of the target object. The approach is tested on CT images of eight patient-specific cases, where cerebral aneurysms, nasal cavities, and an aortic arch are the objects of interest. In the aneurysm cases, the results are compared against constant greyscale thresholding and manual segmentation. The manual segmentations of the aneurysms are validated by a clinical practitioner. Only a qualitative comparison is available for the nasal cavities, and the aortic arch geometries. The results show that the proposed method is effective and capable of extracting the target object in a noisy domain. A sensitivity study is carried out to verify the method's performance with respect to modeling or user choices. The segmentation by the proposed method is also evaluated by performing CFD simulation, including near-wall flow analysis, to ensure that the segmented geometry and the resulting computed solution are representative and meaningful [1).

Accurate segmentation of brain resection cavities (RCs) aids in postoperative analysis and determining follow-up treatment. Convolutional neural networks (CNNs) are the state-of-the-art image segmentation technique, but require large annotated datasets for training. Annotation of 3D medical images is time-consuming, requires highly trained raters and may suffer from high inter-rater variability. Self-supervised learning strategies can leverage unlabeled data for training.

Pérez-García et al. developed an algorithm to simulate resections from preoperative Magnetic resonance imaging (MRIs). They performed self-supervised training of a 3D CNN for RC segmentation using thei own simulation method. They curated EPISURG, a dataset comprising 430 postoperative and 268 preoperative MRIs from 430 refractory epilepsy patients who underwent resective neurosurgery. They fine-tuned the model on three small annotated datasets from different institutions and on the annotated images in EPISURG, comprising 20, 33, 19 and 133 subjects.

The model trained on data with simulated resections obtained median (interquartile range) Dice score coefficients (DSCs) of 81.7 (16.4), 82.4 (36.4), 74.9 (24.2) and 80.5 (18.7) for each of the four datasets. After fine-tuning, DSCs were 89.2 (13.3), 84.1 (19.8), 80.2 (20.1) and 85.2 (10.8). For comparison, inter-rater agreement between human annotators from our previous study was 84.0 (9.9).

They presented a self-supervised learning strategy for 3D CNNs using simulated RCs to accurately segment real RCs on postoperative MRI. The method generalizes well to data from different institutions, pathologies and modalities. Source code, segmentation models and the EPISURG dataset are available at https://github.com/fepegar/resseg-ijcars [2]

Segmentation software

Segmentation software

1)
Goodarzi Ardakani V, Gambaruto AM, Silva G, Pereira R. A porosity model for medical image segmentation of vessels. Int J Numer Method Biomed Eng. 2022 Feb 9:e3580. doi: 10.1002/cnm.3580. Epub ahead of print. PMID: 35142065.
2)
Pérez-García F, Dorent R, Rizzi M, Cardinale F, Frazzini V, Navarro V, Essert C, Ollivier I, Vercauteren T, Sparks R, Duncan JS, Ourselin S. A self-supervised learning strategy for postoperative brain cavity segmentation simulating resections. Int J Comput Assist Radiol Surg. 2021 Jun 13. doi: 10.1007/s11548-021-02420-2. Epub ahead of print. PMID: 34120269.