Building representations of different brain areas through hierarchical point cloud networks

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Abstract

Understanding how the microstructure varies across different brain regions is critical for disease modeling and brain registration. However, current deep learning approaches that work on image data directly may unintentionally focus on textures or other sources of noise in the data and fail to capture meaningful information about the underlying microstructures of interest. In this work, we propose a deep learning method that aims to build salient representations of microstructures inside high-resolution brain imagery data by converting the data to a point cloud format and learning features in this space. We developed a hierarchical PointNet to process extracted 3D point clouds and use it to solve a brain region classification task. We validate our method on a micron-scale neuroimaging dataset, where we generated point clouds from both pixel-level segmentations and simple edge detection methods. In both cases, we show that point cloud-based models achieve better stability and performance when compared to 3D convolutional networks trained on the same brain region classification task. Our results in using "noisier" data from simple filtering operations provides initial evidence that point cloud representations could be a lightweight and data-efficient approach for brain parcellation.

Keywords: Neuroanatomy, Point Cloud, Deep Learning, PointNet, Brain Parcellation.

1. Introduction

Models of neuroanatomy provide essential information that facilitates tasks such as disease mapping, brain alignment, and brain parcellation (Eickhoff et al., 2018). Understanding how microstructure varies within different brain regions sits at the core of these tasks, which is empowered by the advances of neuroimaging techniques. Typically, deep learning methods extract representations of the brain by processing images directly. However, learned representations might neglect the fine-scale details of the microstructures within the brain, such as cell bodies or axons. Instead, these representations focus on other properties in the image (like textures) which could be domain specific and fail to generalize (Schawkat et al., 2020). Moving forward, deep learning approaches that can build rich models from microstructural components are needed for refining our understanding of the brain's architecture in healthy and diseased states.

Here, we show how point cloud-based representation learning can provide a path forward in the analysis of volumetric brain imaging data. For this study, we adapted a hierarchical point cloud learning method called PointNet++ (Qi et al., 2017), which learns fine-grained patterns from unordered point sets, to build representations of brain microstructures generated both from large-scale annotations and from simple edge detection filters. We tested

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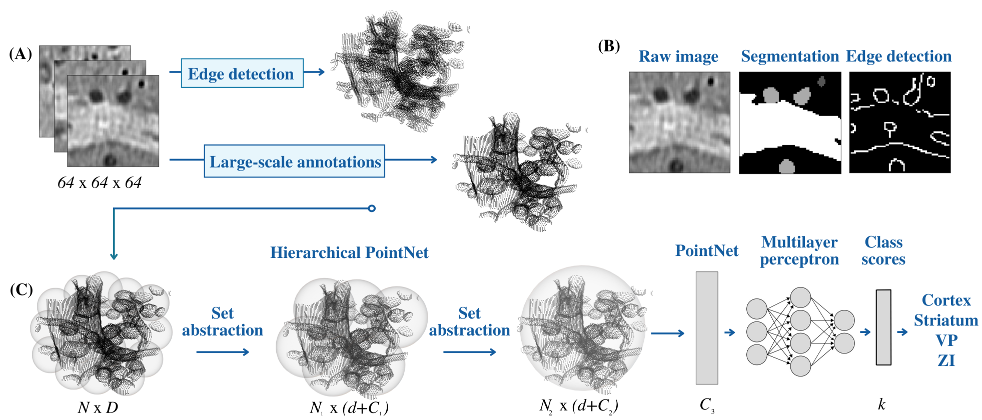

Figure 1: *Overview of the pipeline.* (A) We extract point cloud from images through large-scale annotations and edge detection. (B) Image examples of segmentation through annotations and edge detection results. (C) PointNet++ learns point cloud representation through hierarchical set abstraction.

our model on a brain classification task in a three-dimensional micron-scale X-ray microCT dataset spanning multiple brain areas from thalamus to cortex (Prasad et al., 2020) where the goal is to classify small 3D volumes into one of four brain areas (learn a parcellation). Our results demonstrate that even in the absence of large-scale annotations, point clouds generated from simple edge detection operations are a viable option for brain-area classification task, providing comparable or better performance than 3D convolutional networks.

2. Method and Data

We use a publicly accessible X-ray microCT dataset (Prasad et al., 2020) that contains abundant information about rich brain structures (axons, cell bodies, blood vessels) in three dimensions. The dataset spans multiple brain regions, each containing a unique distribution of different underlying microarchitectural components, which enables the model to learn meaningful features of the neuroanatomy to classify samples into different brain regions.

To test our ability to solve the brain area classification task, we generated point clouds from our imaging dataset using two approaches (Fig.1(A, B)). First, we generated point clouds from large-scale manually proofread annotations assisted by a U-Net (Balwani et al., 2021). In this case, we applied the Marching Cubes' algorithm (Lewiner et al., 2003) on the manually proofread segmentations to extract the outer boundary of all the segmented microstructures. Second, we wanted to test a simple strategy where we generated a point cloud by detecting microstructural edges from the raw image volume after applying a Canny edge filter with $\sigma = 2.5$ and thresholding the image (see the top of Fig.1(B)).

After building point cloud estimates of microstructures in our imaging data, we pass the point clouds through a hierarchical architecture called PointNet++ (Qi et al., 2017) (see Fig.1(C)). The model learns from an unordered set of points $\{x_1, x_2, \ldots, x_N\}$ with $x_i \in \mathbb{R}^D$ based on a hierarchical learning approach: the network partitions the point cloud into overlapping local regions and extracts localized features from neighbouring points in each layer. The grouped points are spatially downsampled with increased dimensionality (Set abstraction), and the learned features are aggregated at the end and processed by another PointNet. PointNet transforms the resulting feature set $\{l_1, l_2, \ldots, l_{N_2}\}$ with a set function $f(l_1, l_2, \ldots, l_{N_2}) = g(\max\{h(l_i)\})$, where g and h are multi-layer perceptrons (MLPs).

Table 1: Classification accuracies and standard deviation.

		Volume (3d-ConvNet)			*Annotated Edges*		*Detected Edges*	
		3layer	4layer	5layer	PtNet	PtNet++	PtNet	PtNet++
no-Aug	Acc	76.89	82.47	76.71	63.40	**82.87**	62.07	**87.61**
	Std	16.95	10.13	24.69	2.20	**0.74**	1.66	**0.95**
with-Aug	Acc	72.73	**88.21**	80.18	58.19	86.19	62.14	**89.72**
	Std	10.48	5.69	7.13	1.65	**0.71**	1.51	**1.23**

3. Evaluations

Several non-overlapping imaging volumes (of size 256×256×256) from four different brain regions (the cortex, striatum, ventral posterior (VP), and zona incerta (ZI)) were selected and annotated for model evaluation. Each block was further divided into 343 volumes of size 64×64×64 with 32 pixels of overlap. Given n 256×256×256 blocks in a region, one block from each region was selected as the testing set, while 343 volumes of size 64×64×64 were randomly sampled from the remaining $n-1$ blocks for each region as the training set. We trained 3D convolutional nets of three different depths (3, 4, 5 layers), PointNet, and PointNet++ using an Adam optimizer with learning rate 0.00001 for 200 epochs. Table 1 compares the classification accuracy and standard deviation of training over 5 different random seeds without (no-Aug) or with data augmentation (with-Aug).

Our results show that PointNet++ gives much higher performance than PointNet, and better or comparable performance than 3D ConvNets of different depth. Overall, point cloud based approaches provide much better stability than their image-based counterparts (3D ConvNets). Surprisingly, point clouds generated from detected edges give better performance than those from annotations. Compared to imaging volumes, point clouds contain less redundant data and thus less storage. Thus, leveraging this sparse data format for tasks such as brain area or disease classification could expand approaches for brain mapping.

References

Aishwarya Balwani et al. Multi-scale modeling of neural structure in x-ray imagery. In *IEEE ICIP*, pages 141–145, 2021.

Simon B. Eickhoff et al. Imaging-based parcellations of the human brain. *Nature Reviews Neuroscience*, 19(11):672–686, 2018.

Thomas Lewiner et al. Efficient implementation of marching cubes' cases with topological guarantees. *Journal of Graphics Tools*, 8(2):1–15, 2003.

Judy A Prasad et al. A three-dimensional thalamocortical dataset for characterizing brain heterogeneity. *Scientific Data*, 7(1):1–7, 2020.

Charles R Qi et al. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. *NeurIPS*, 30, 2017.

Khoschy Schawkat et al. Diagnostic accuracy of texture analysis and machine learning for quantification of liver fibrosis in MRI: correlation with MR elastography and histopathology. *European Radiology*, 30(8):4675–4685, 2020.