Novel Model-Based and Deep Learning Approaches to Segmentation and Detection in 3D Microscopy Images

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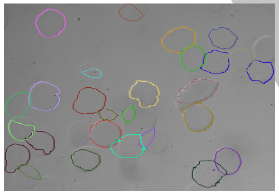
Thesis Defense

July 20th , 2020

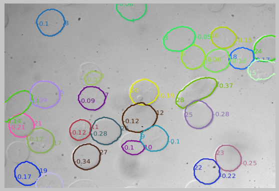
School of Electrical and Computer Engineering

OVERVIEW

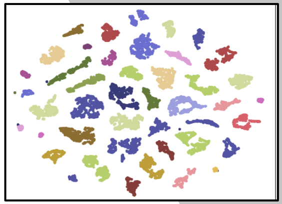
- **Introduction**
  - Problem statement
  - Preliminary work
- **Void and Fiber Segmentation Using Deep Learning**
  - Voids: 3D semantic segmentation
  - Fibers: 3D embedded learning
- **3D Fiber Detection using centroid regression**
  - Center regression
  - 3D object proposals
- **Summary**
  - Thesis contributions
  - Published works



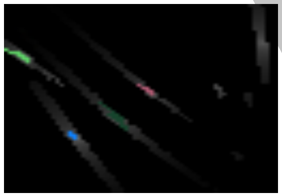
MPP + AC



MPP + LS



Embedded learning

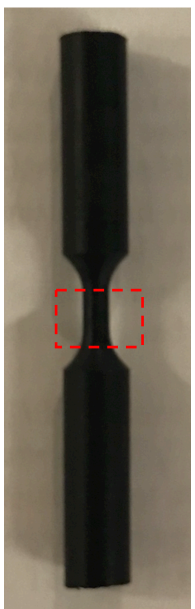


Center regression

INTRODUCTION

Objective:

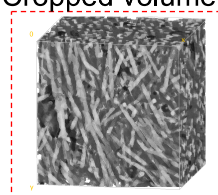
Characterization of glass fiber reinforced composite:

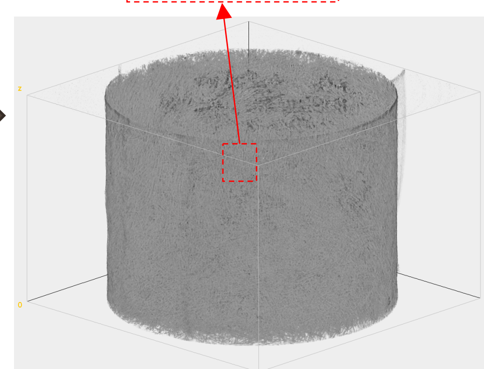


[Dupont]

Tomography & reconstruction

Cropped volume



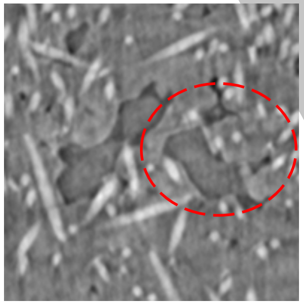


Raw Volume

Structural & mechanical characterization

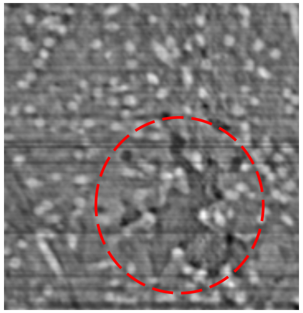
CHALLENGES

- Large number of objects
  - Arbitrary size/orientation
  - Regular and irregular shapes
- Low contrast
- Imaging & reconstruction noise
- No ground truth
- Large volumes



Low contrast void

Ring artifact



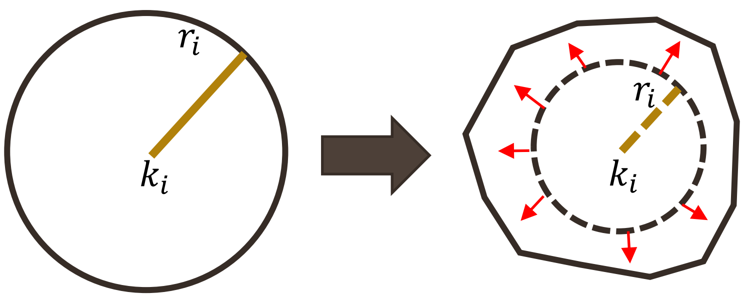
Irregular volumes

[ACME Lab Purdue]

PRELIMINARY WORK: MODEL BASED SEGMENTATION: ACTIVE CONTOURS MPP

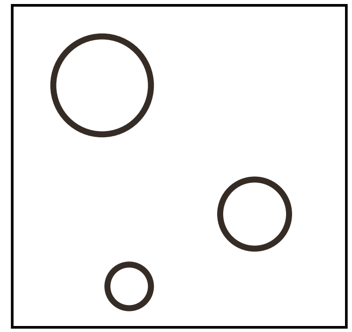
Marked point process & active contours

Sample Object $\omega_i = (k_i, r_i)$

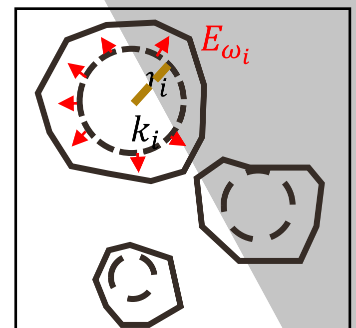


ω_i: marked ith object
k_i: $\omega_i's$ (x, y) coordinate
r_i: $\omega_i's$ radious

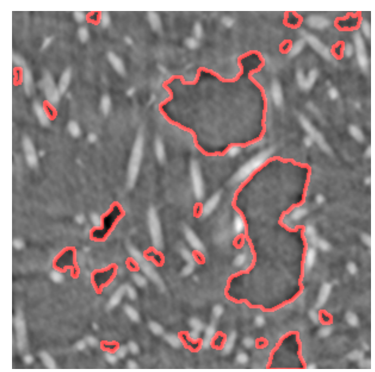
Sample deformed object $\widehat{\omega}_i$



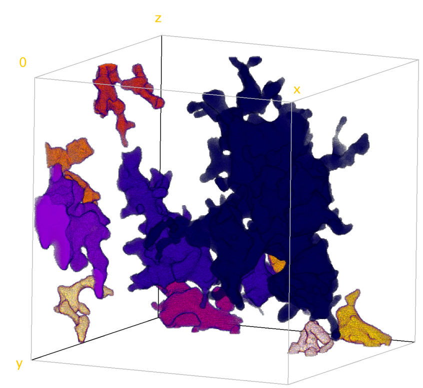
Sample MPP



Sample MPP + AC



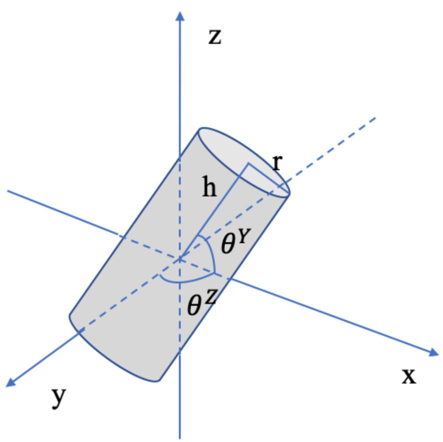
Sample results

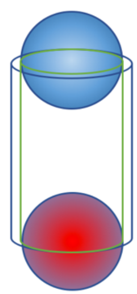


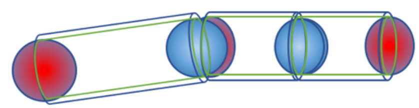
2.5D results

TIANYU'S WORK: FIBERS: CONNECTED TUBE MPP

- Model fibers as **connected tubes**

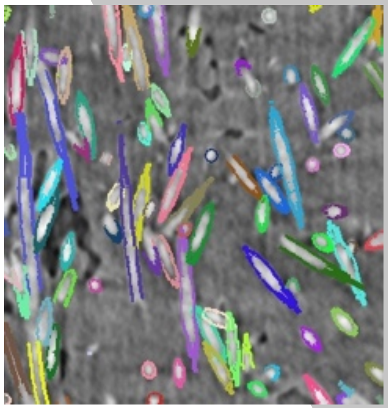




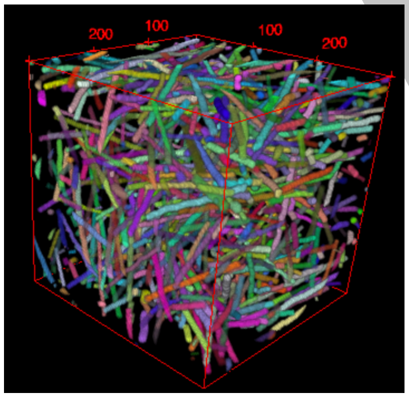


$$\omega_i = (k_i, r_i, h_i, \theta^Y, \theta^Z)$$

ω_i: marked ith object
k_i: $\omega_i's$ (x, y) coordinate
r_i: $\omega_i's$ radious
h_i: $\omega_i's$ length
θ_i^Y: $\omega_i's$ orientation with respect to XY plane
θ_i^Z: $\omega_i's$ orientation with respect to Z axis



2D cross section

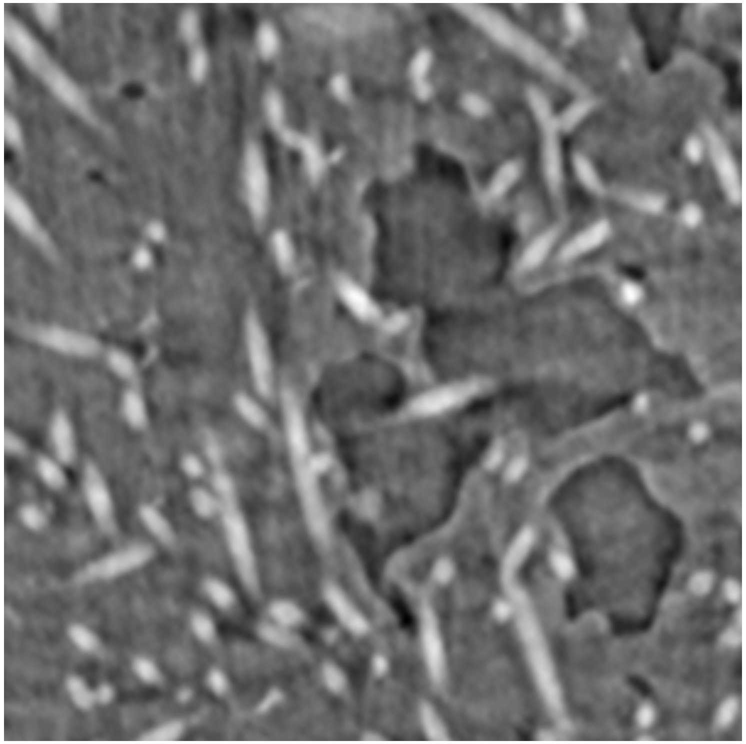


3D view

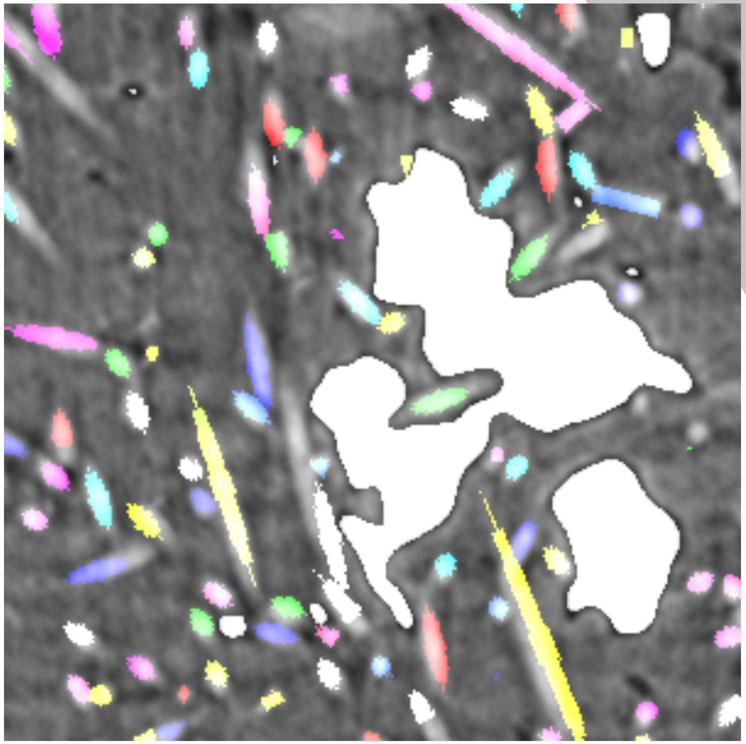
Li [1]

SAMPLE RESULTS OF MPP

Colors: fiber instances
White: voids



Original Image



Model Based Output

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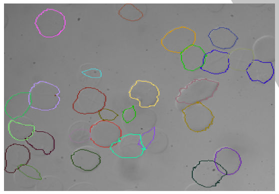
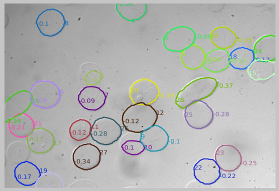
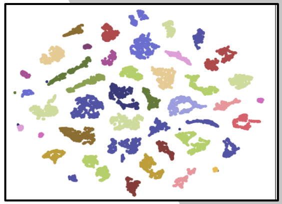


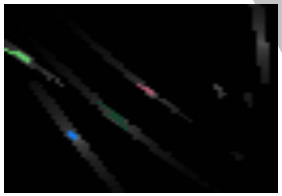
MPP + AC



MPP + LS



Embedded learning



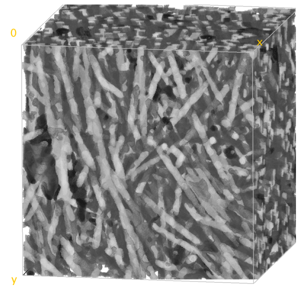
Center regression

DRAWBACKS OF MPP: COMPUTATION TIMES

MPP: Marked point process

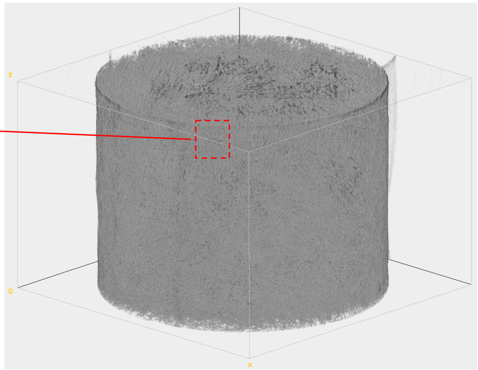
Computation Times*:

Window Size	Voxels	MPP Fibers	MPP Voids
140 micron	300x300x300	18 mins	3 mins
700 micron	500x500x500	6 hours	20 mins
1900 micron	2500x2500x1300	19 days**	26 days**



300 voxels

300×300 voxels



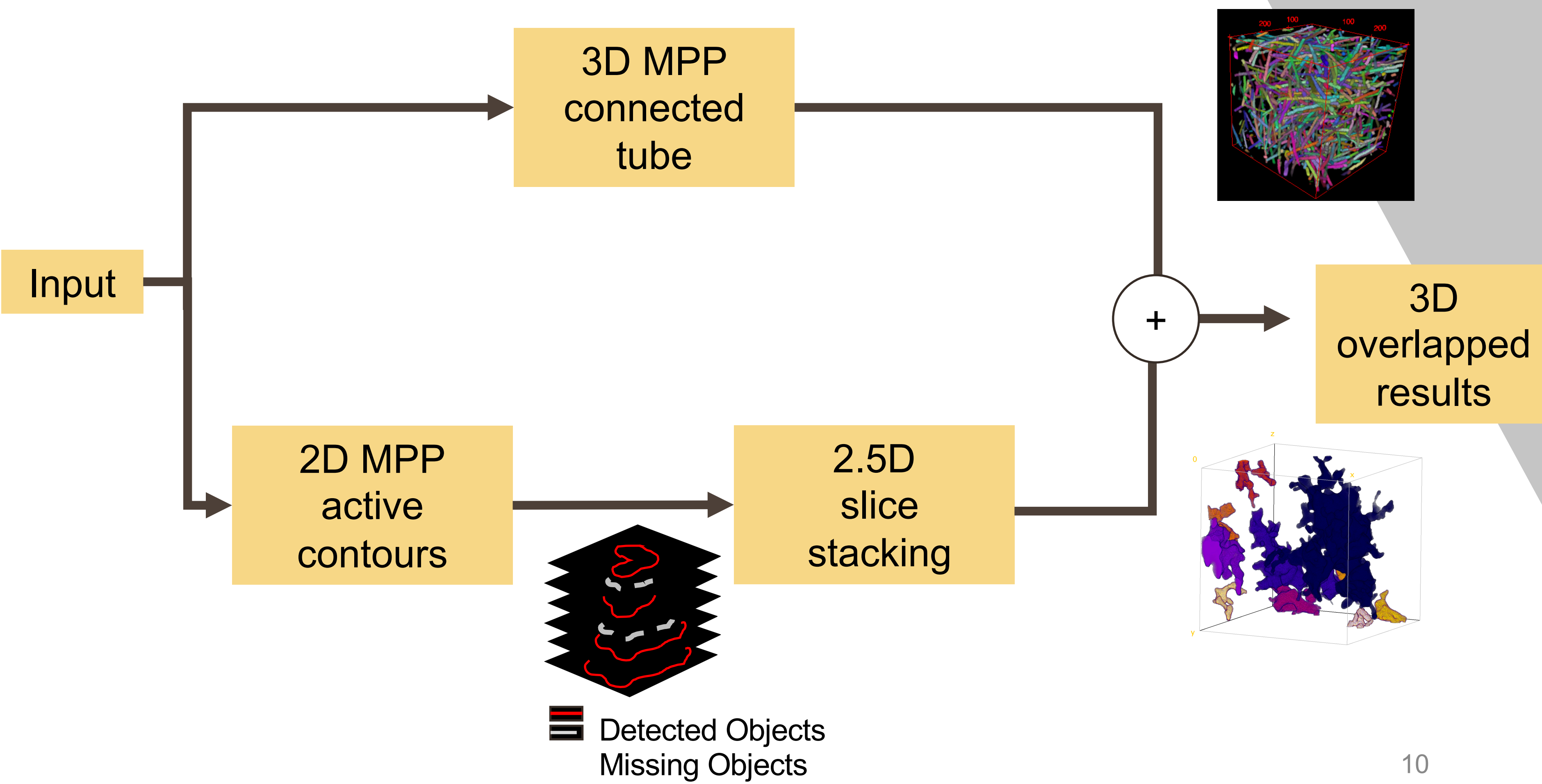
1350 voxels

2025×2025 voxels

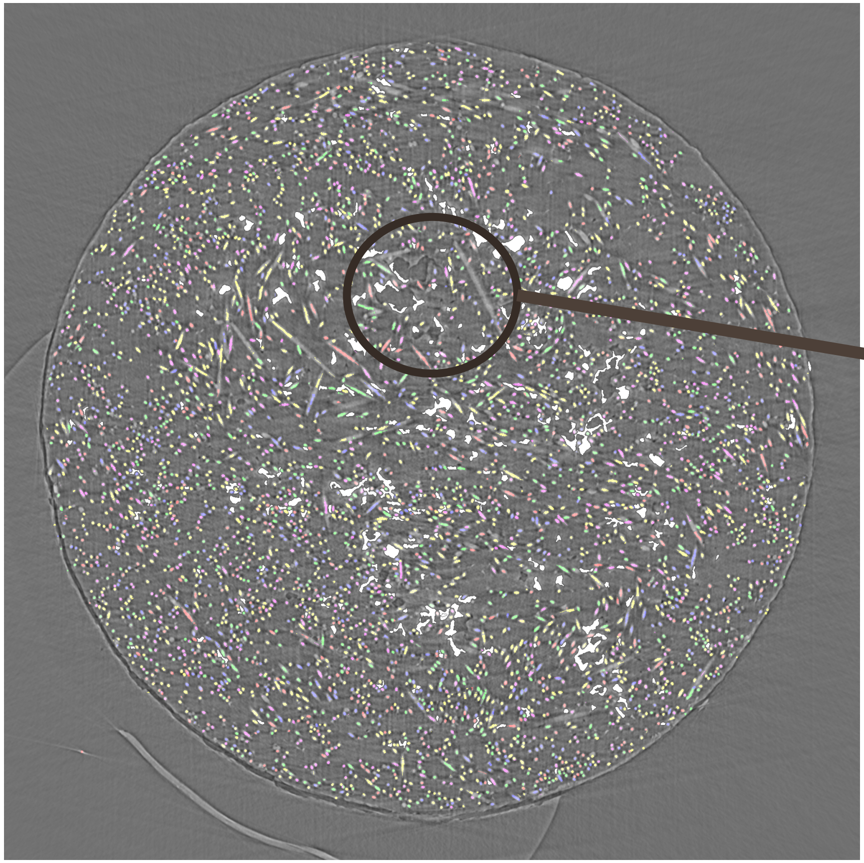
* Measured in Rice cluster: single core Intel Xeon-E5 processor

** Estimated for single core from parallel implementation using 20 cores

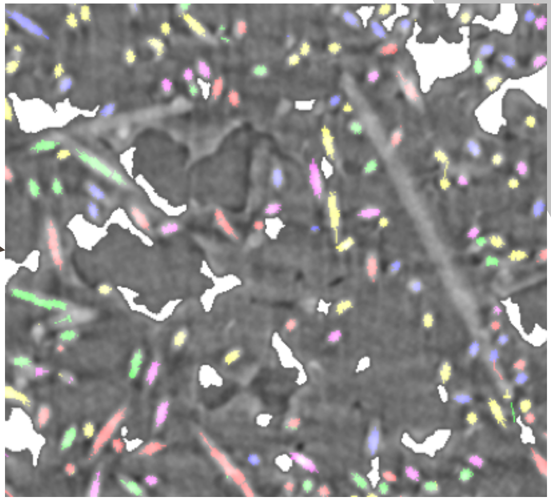
DRAWBACKS OF MPP: SEPARATE MODELS



DRAWBACKS OF MPP: PARAMETER DEPENDENT NOT PRECISE



Sample volume



Magnification

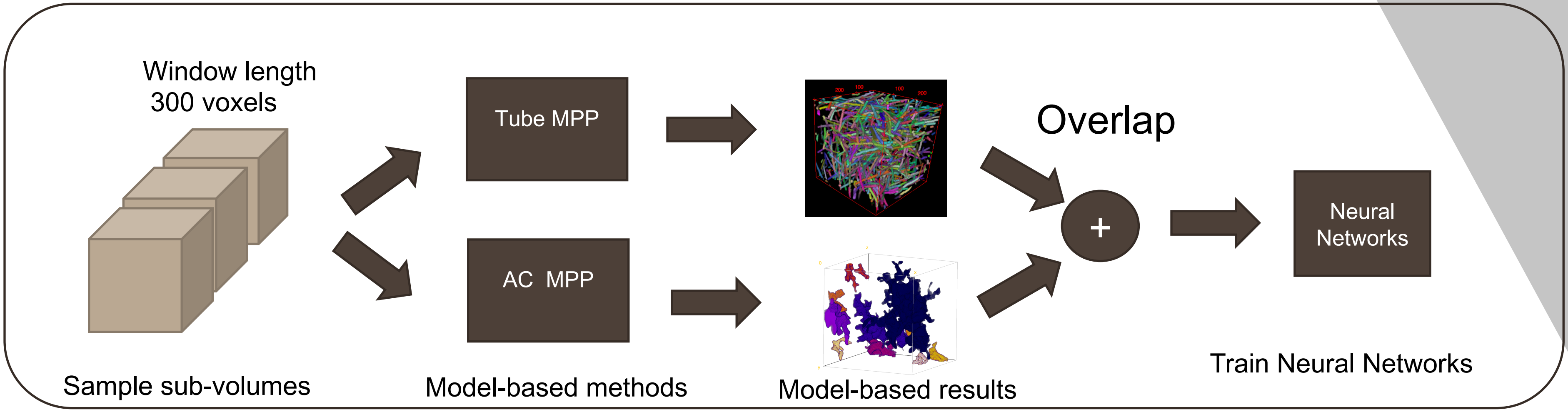
VOID AND FIBER SEGMENTATION USING DEEP EMBEDDING LEARNING

Objective:

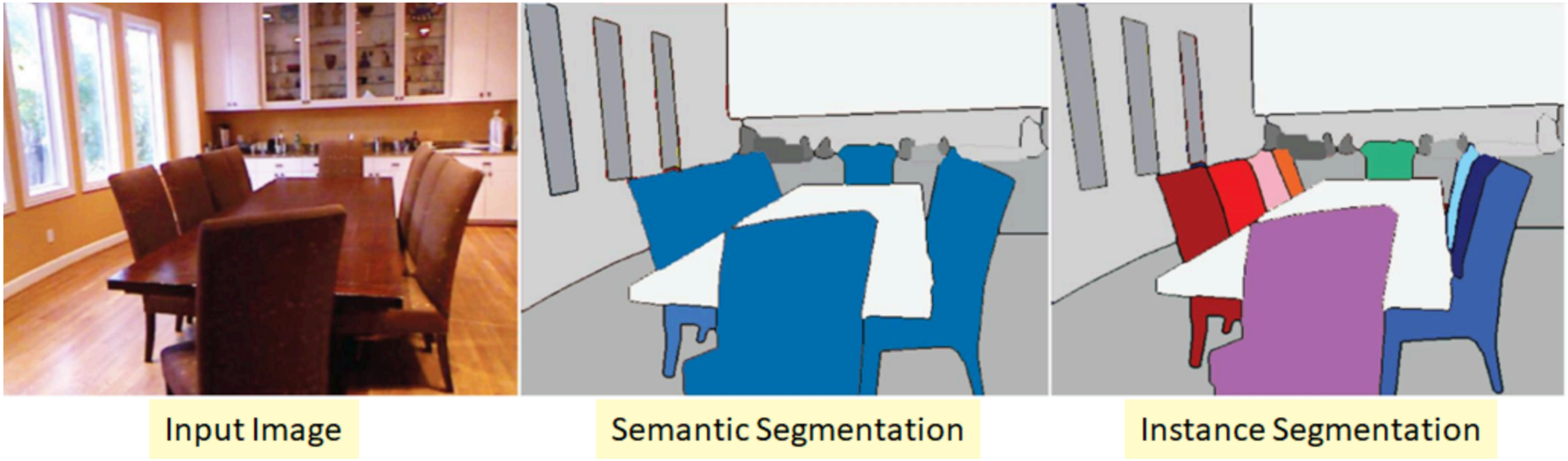
- Obtain semantic and instance segmentation
- Unify framework for voids and fibers
- Speed up inference time
- Refine segmentation

PROPOSED SURROGATE METHOD:

Network training with model-based-results:

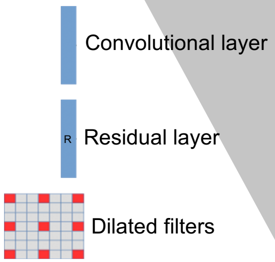


SEMANTIC SEGMENTATION

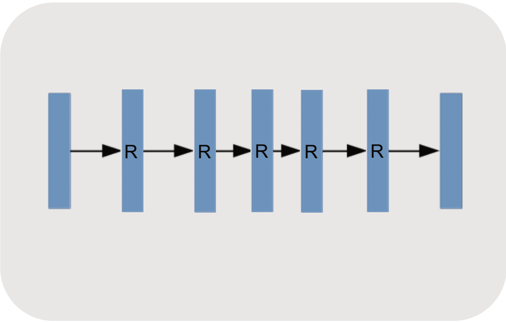


Abel [2]

POPULAR ARCHITECTURES FOR SEMANTIC SEGMENTATION



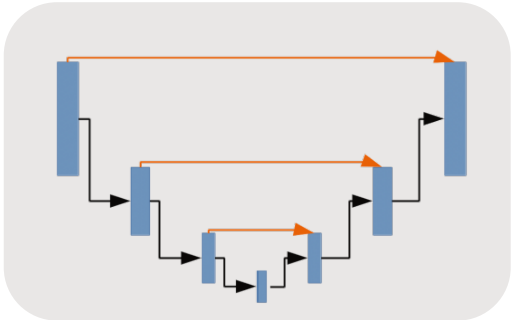
R-Net



Konopczyński[3]

- Residual layers
- Captures local information
- High memory requirements

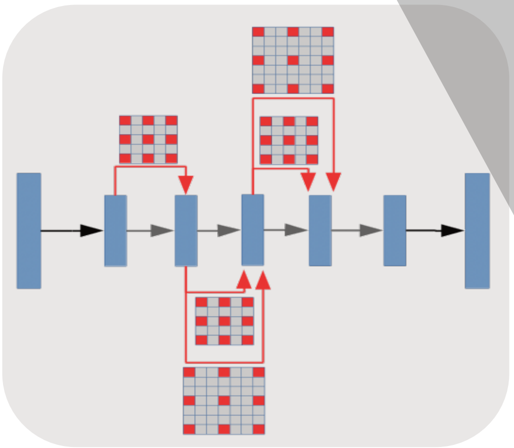
U-Net



Ronneberger[4]

- Skipped connections
- Captures local & contextual information
- Low memory requirements

DeepLabv3



Chen[5]

- Dilated filters
- Captures contextual information
- Low memory requirements

COMPARISON FOR SEMANTIC SEGMENTATION

f1 score:

$$f1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

TP: true positive, FP: false positive, FN: false negative

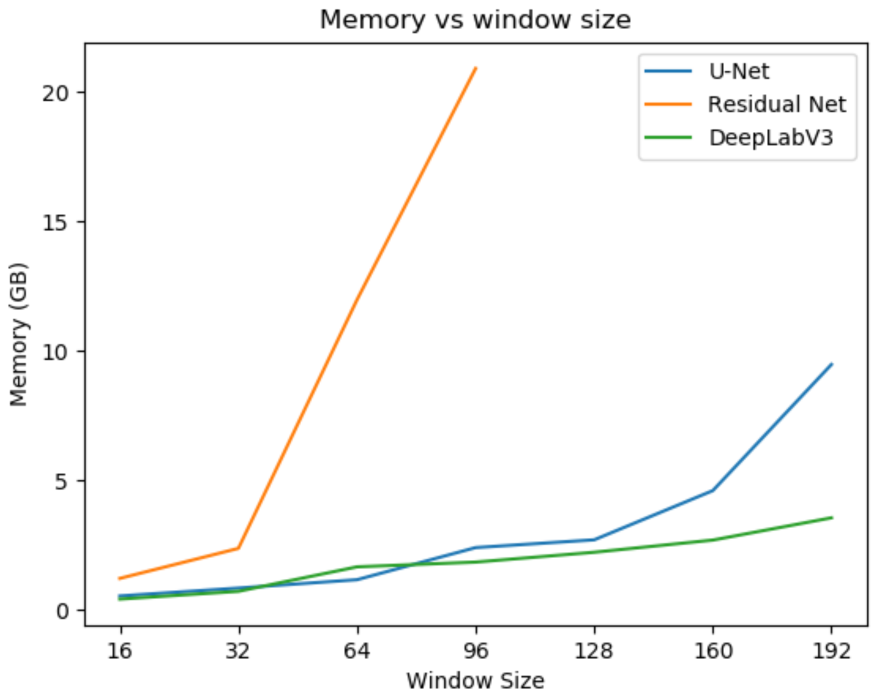
- Measures pixel-wise accuracy

- 0: lowest precision/recall
- 1: best precision/recall

Method	f1 fibers	f1 voids
U-Net*	0.809	0.622
Residual Net**	0.326	0.067
DeeplabV3*	0.420	0.701

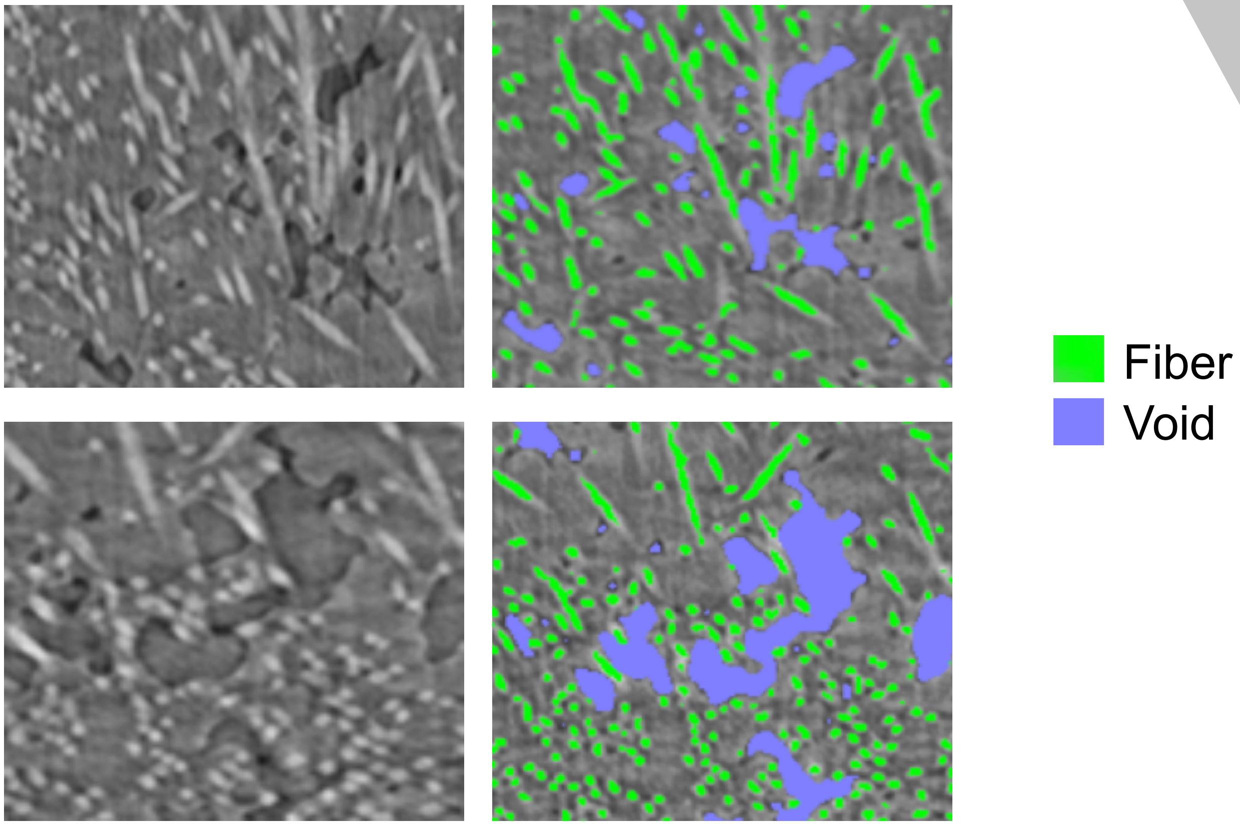
*window size = 192

**window size = 96

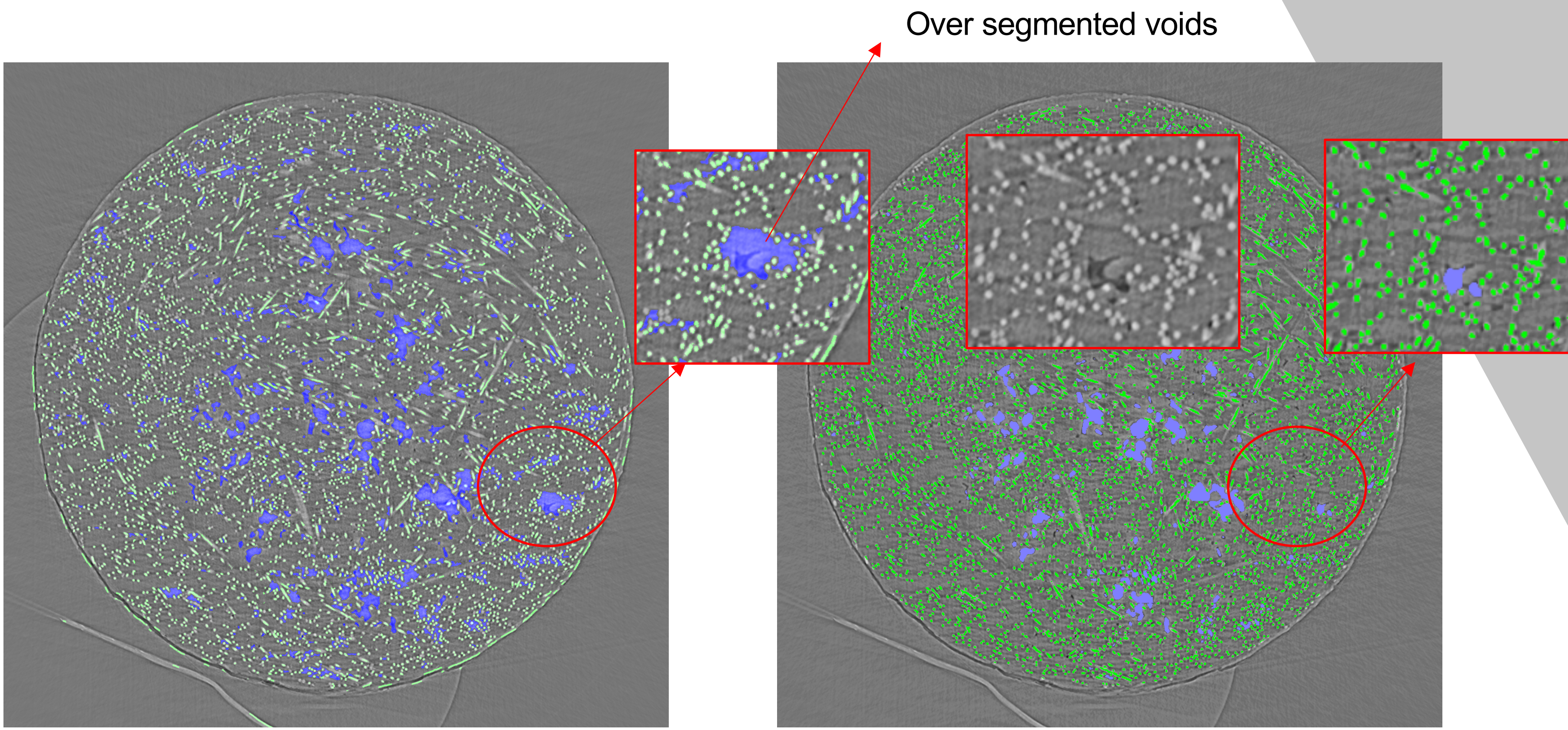


Trained and tested in GPU NVIDIA-TITAN RTX with **25 GBs** of memory

SEMANTIC SEGMENTATION: RESULTS

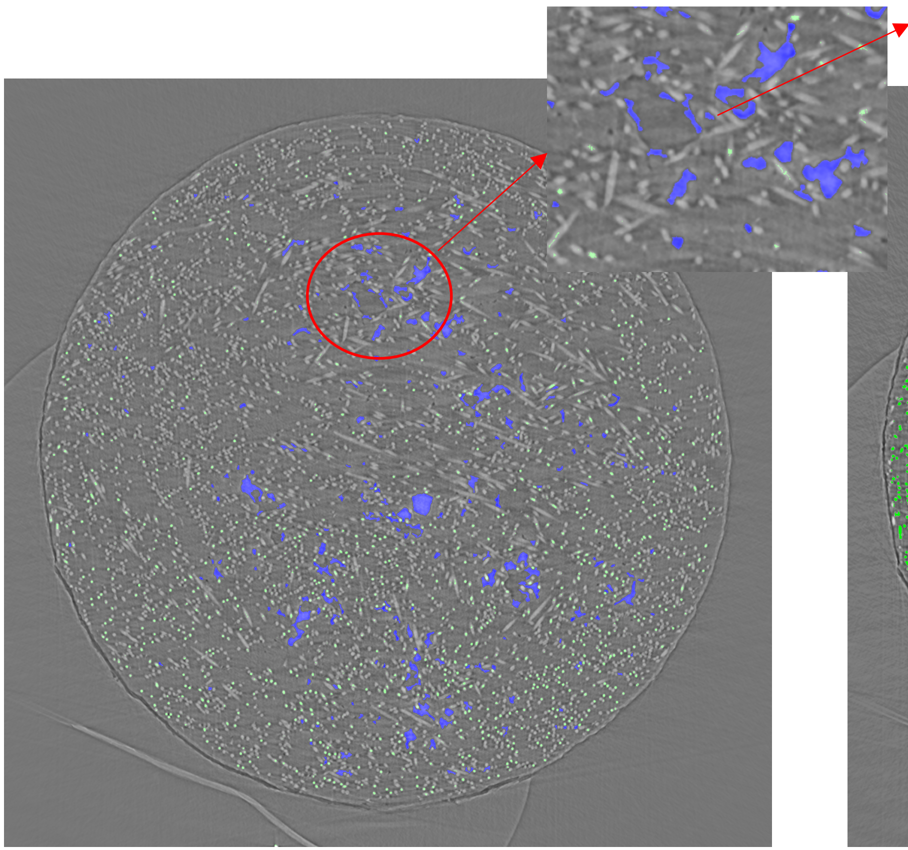


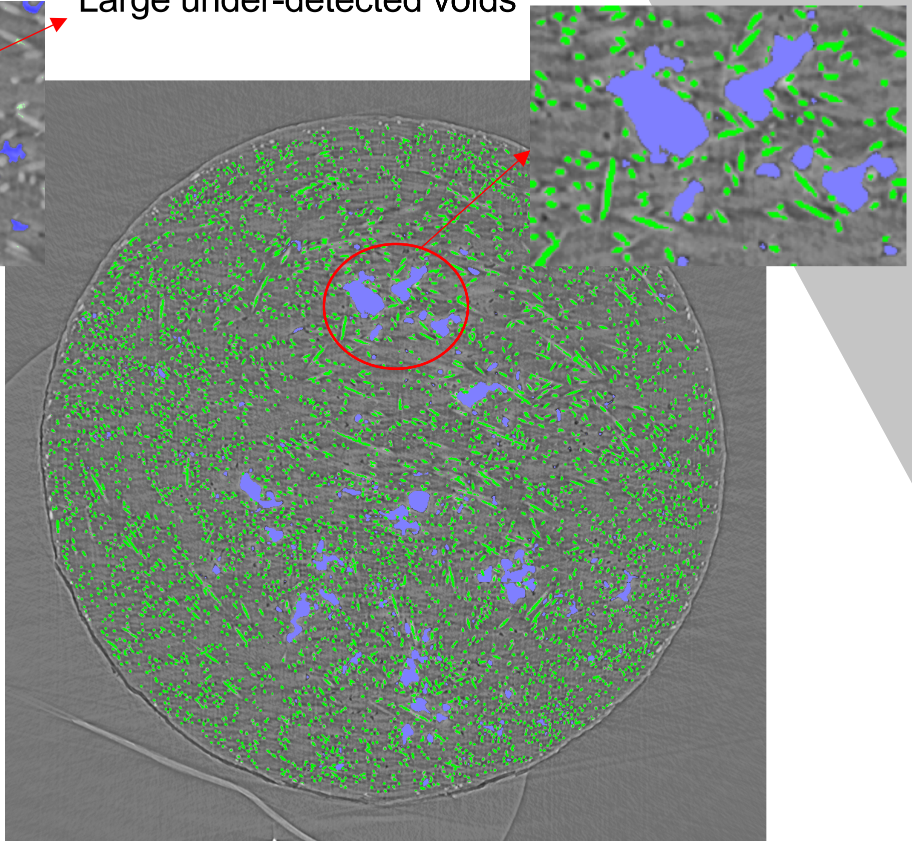
RESULTS COMPARED TO TRAINING DATA



Model Based Methods $\mu_{intensity} = 120$ CNN Outputs

RESULTS COMPARED TO TRAINING DATA



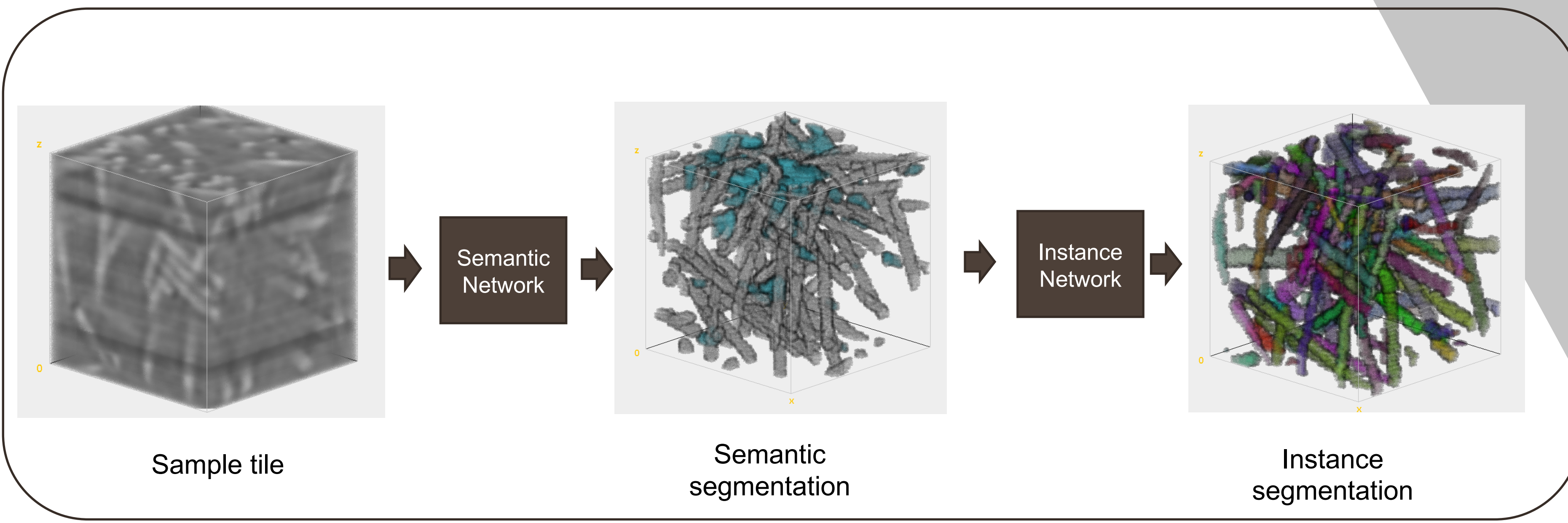


Model Based Methods

CNN Outputs

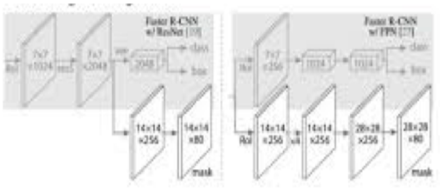
$\mu_{intensity}$ = 70

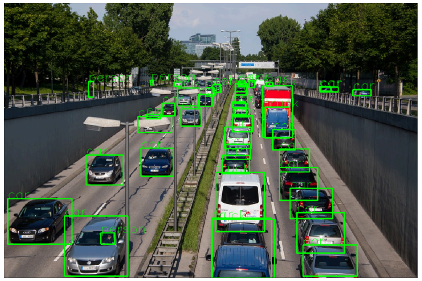
INSTANCE SEGMENTATION



APPROACHES FOR 3D INSTANCE SEGMENTATION

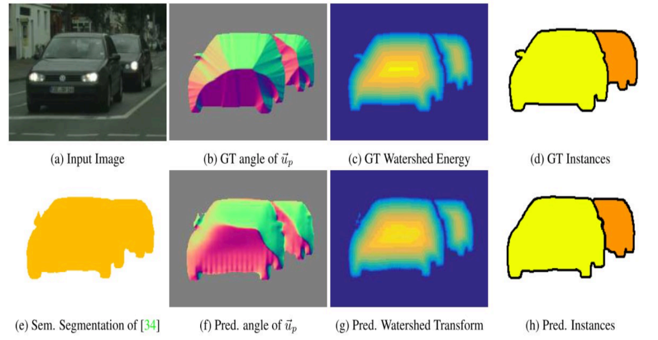
- **3D R-CNN**
  - Object Proposal
  - Marks regression





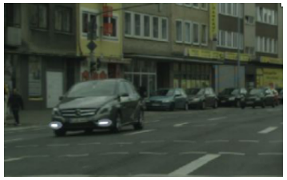
Ren[6]

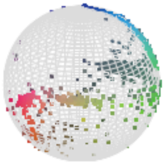
- **3D Deep Watershed**
  - Optimal watershed energy estimation
  - Apply Watershed postprocessing



Bai[7]

- **Embedded space**
  - Output embedded channels
  - Use clustering algorithms on embedded channels



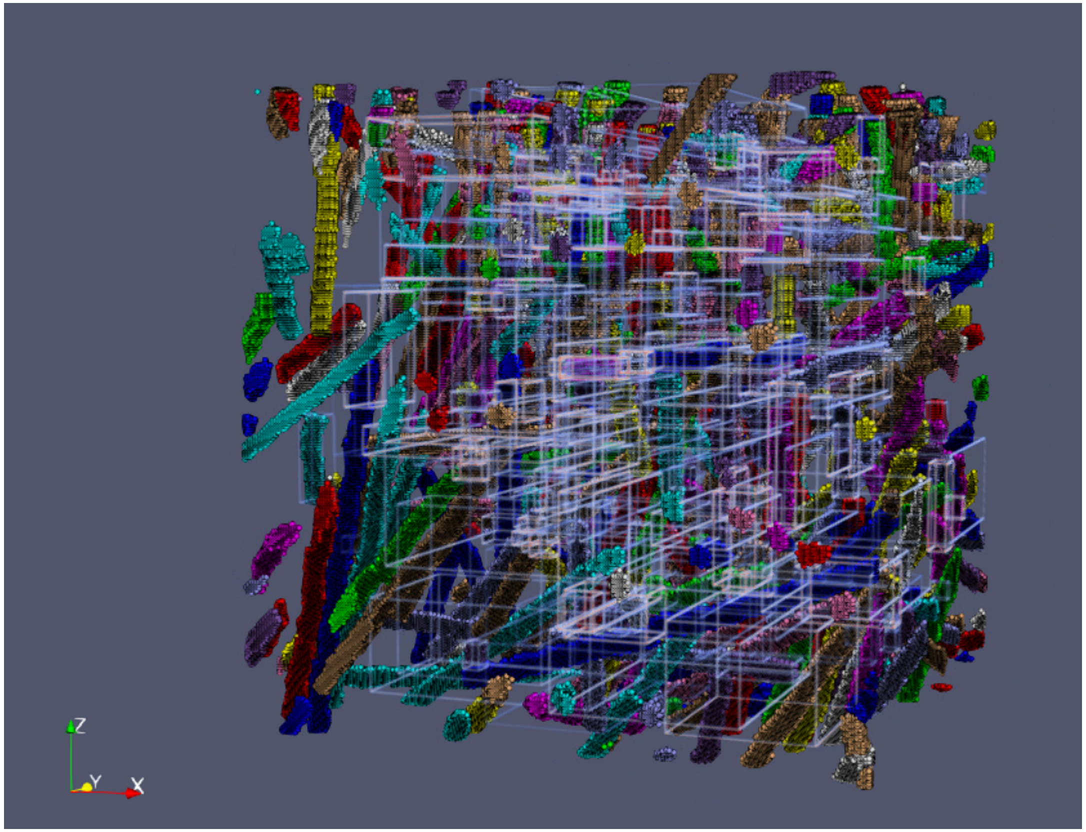


Bert De Brabandre[8]

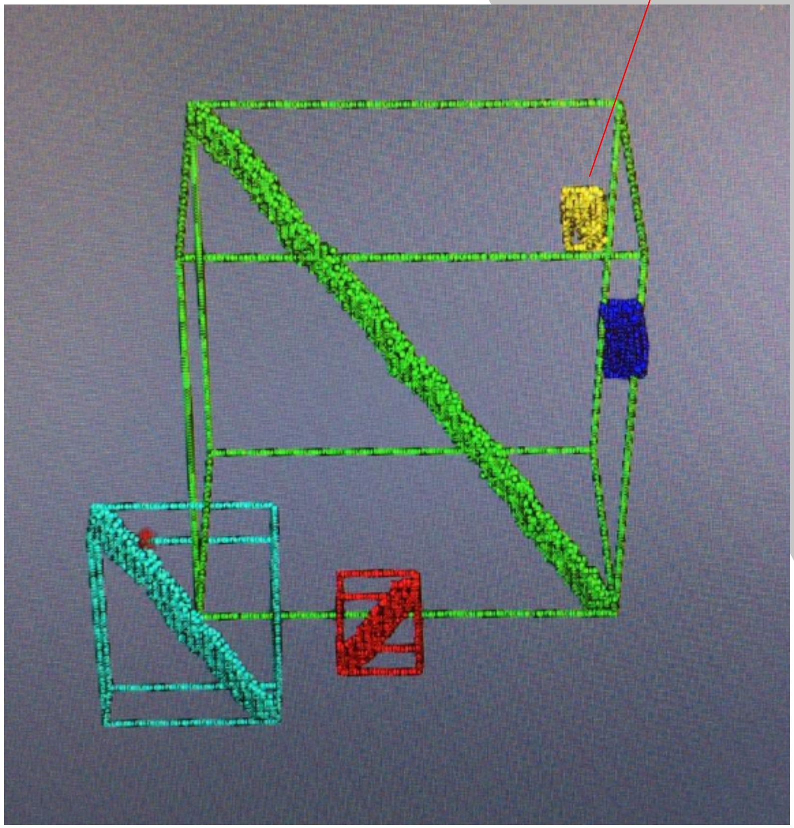
MASK RCNN CONSTRAINS

Dense subvolumes
Broken objects

Full Volume bounding boxes

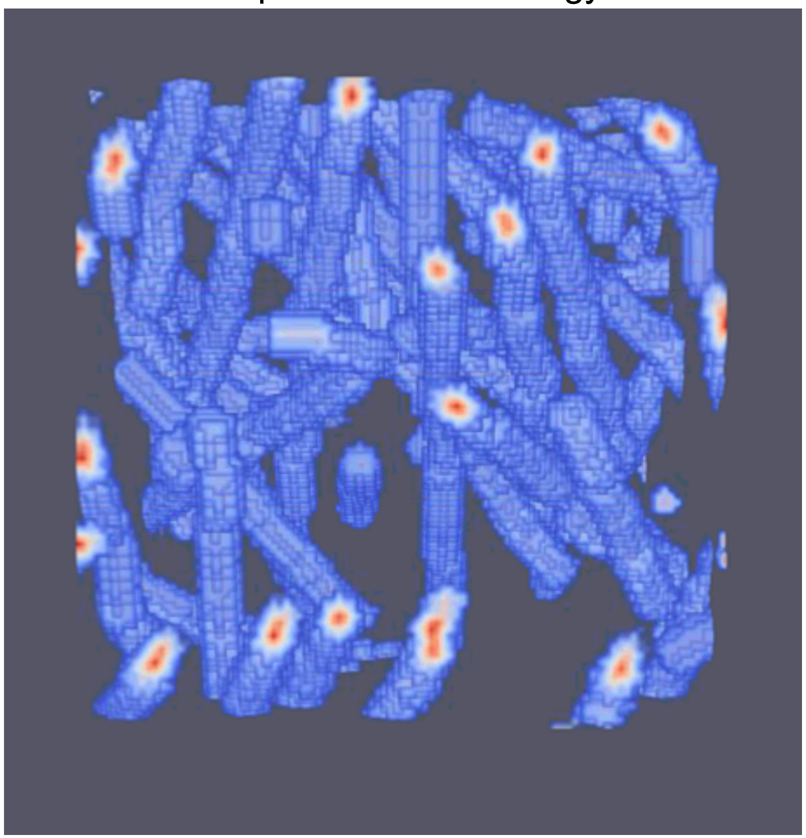


Sample bounding boxes

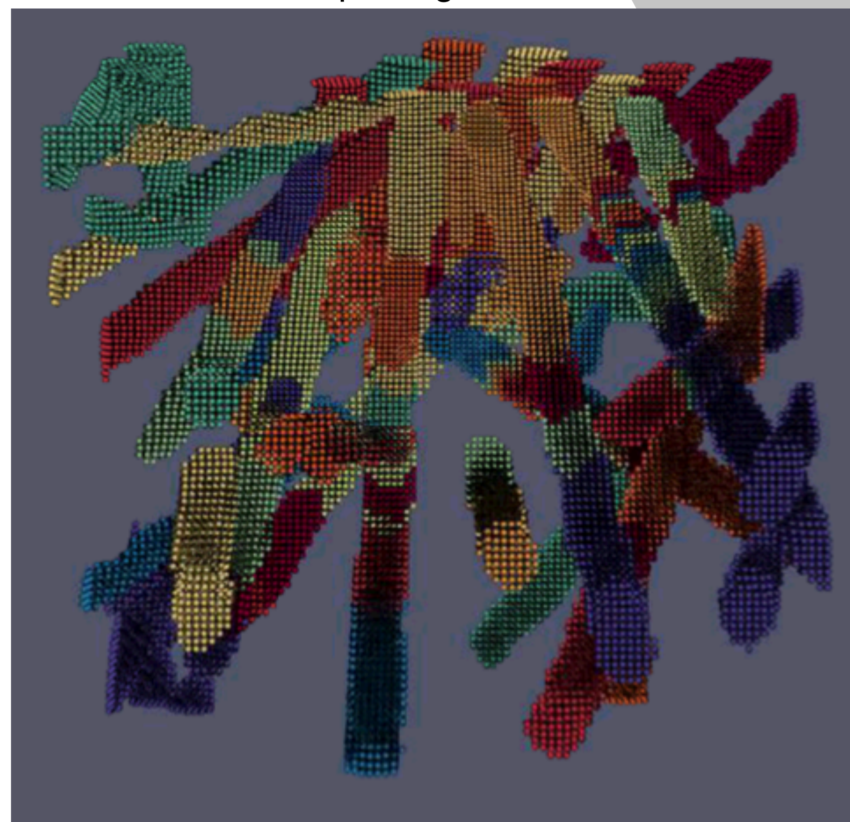


DEEP WATERSHED CONTAINS

Sample watershed energy

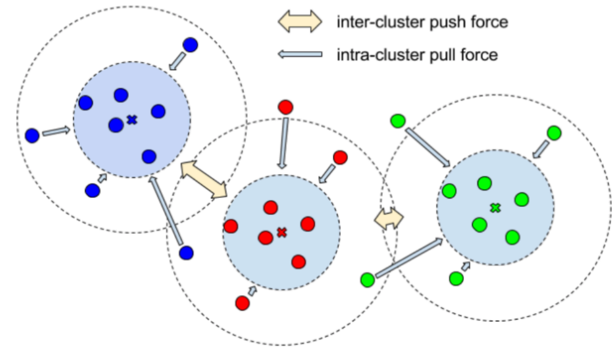


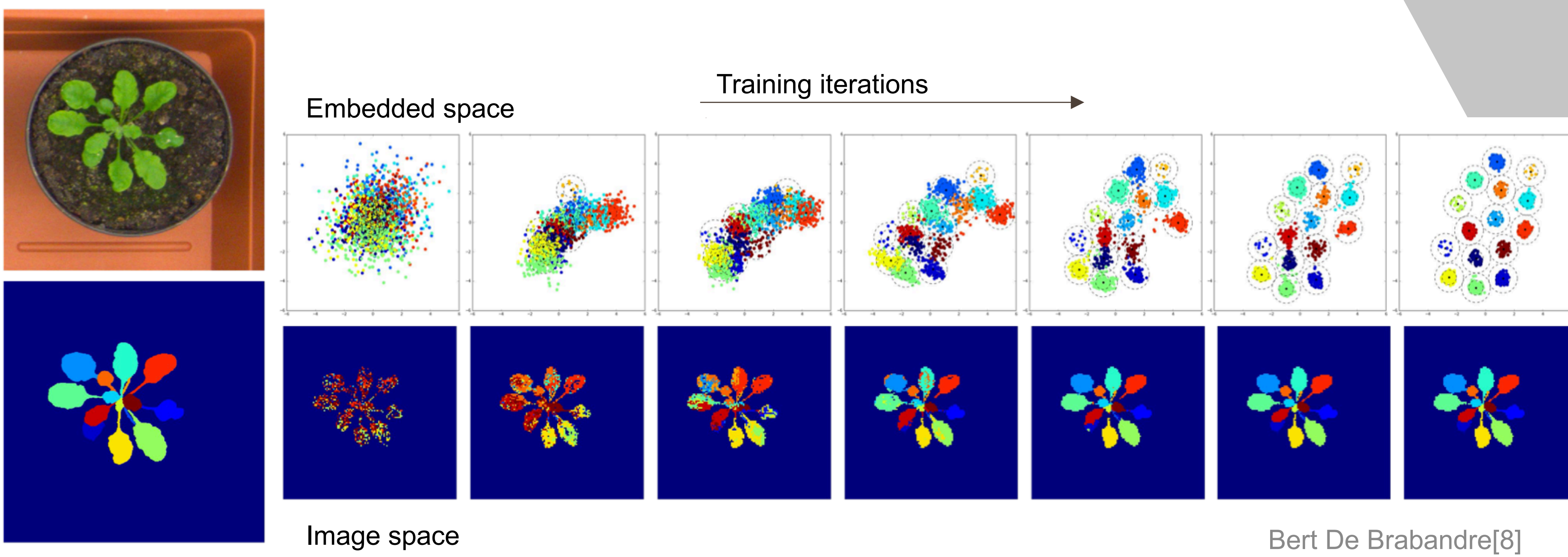
Sample segmentation



FEATURE EMBEDDED LEARNING

- Learns to separate instance voxels in latent feature space
- A clustering algorithm is applied to separate instances





Bert De Brabandre[8]

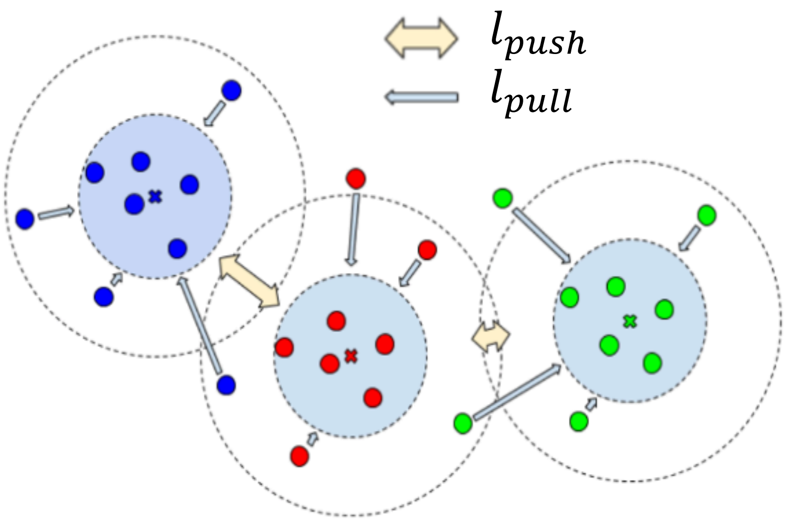
EMBEDDED LEARNING LOSS

$$l_E = l_{pull} + l_{push} + l_{reg}$$

$$l_{pull} = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{|S_c|}\sum_{e_i \in S_c}\left(\|e_i - \mu_c\|_2^2 - \delta_v\right)_+$$

$$l_{push} = \frac{1}{C(C-1)}\sum_{i=1}^{C}\sum_{j=1}^{C}\left(\delta_p - \|\mu_i - \mu_j\|_2^2\right)_+$$

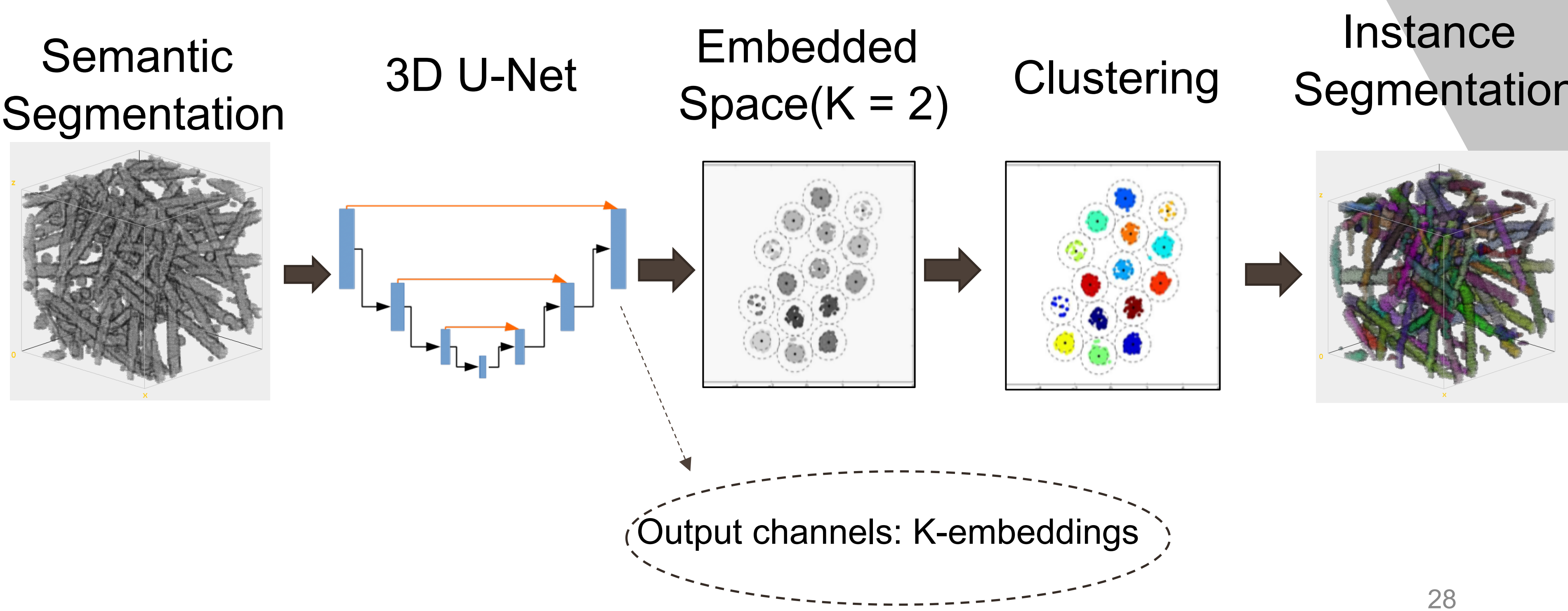
$$l_{reg} = \frac{1}{C}\sum_{c=1}^{C}\|\mu_c\|_2$$



Bert De Brabandre[8]

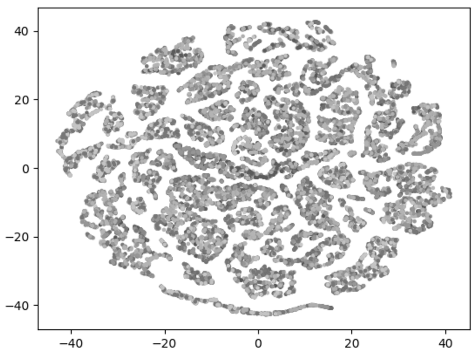
C: Number of instances/clusters
μ_c: c^{th} cluster center
S_c: Set of voxels representing instance c
e_i: i^{th} embedded voxel output
$(a)_+ = \max(a, 0)$

EXTEND U-NET TO DETECT INSTANCES

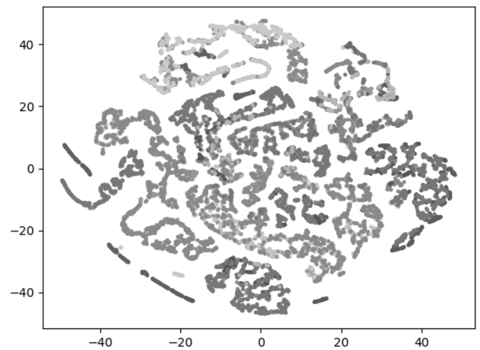


Reduced dimensionality for display with (t-SNE)

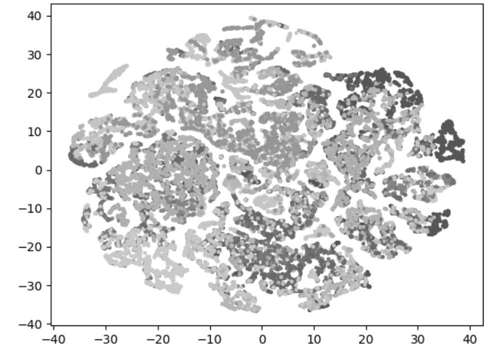
LEARNING EMBEDDED SPACE (K = 12)



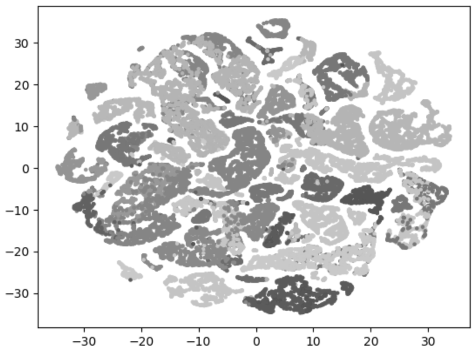
Iteration n=0



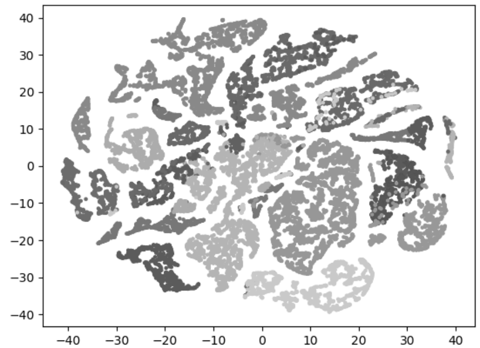
n=10



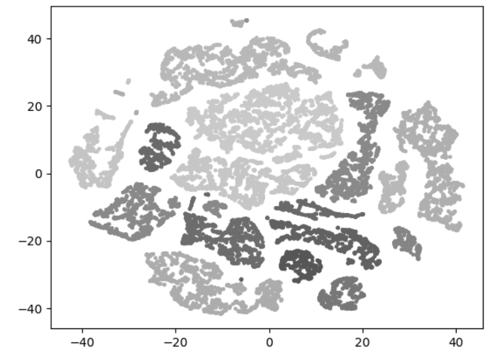
n=50



n=100



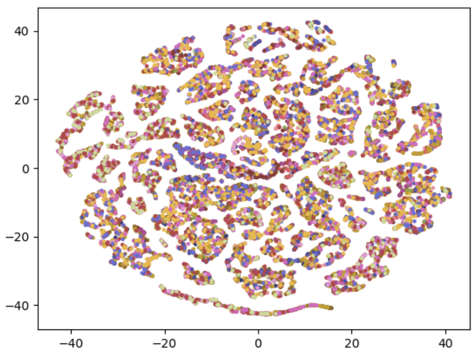
n=500



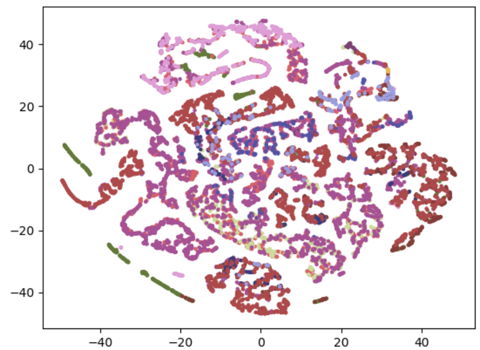
n=2000

Reduced dimensionality for display with (t-SNE)

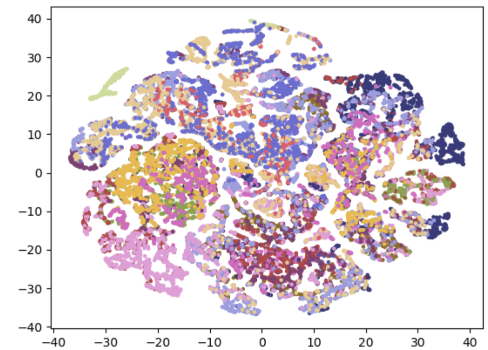
LABELED EMBEDDED SPACE (K = 12)



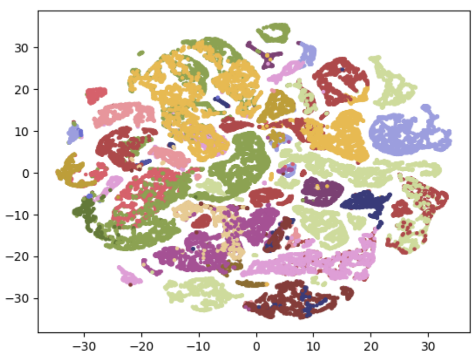
Iteration n=0



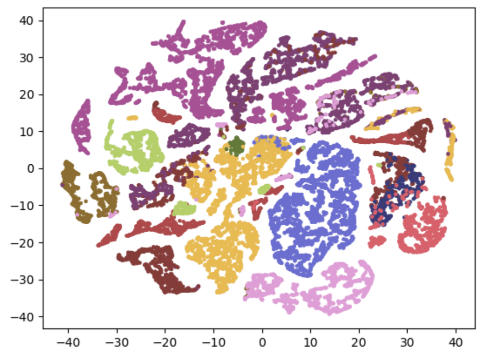
n=10



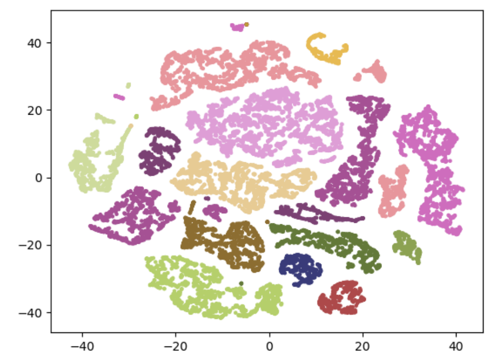
n=50



n=100



n=500

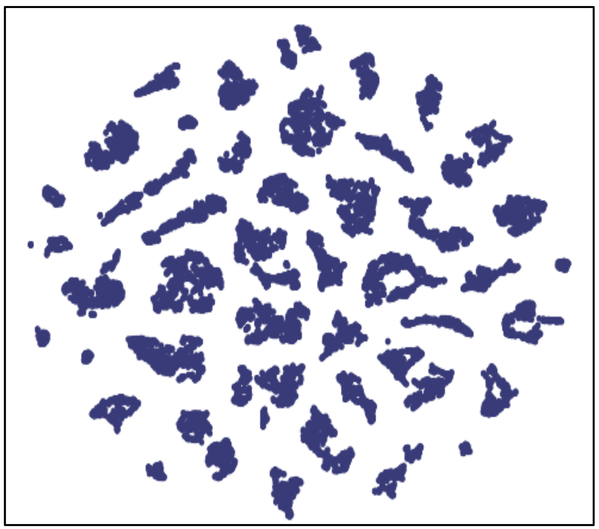


n=2000

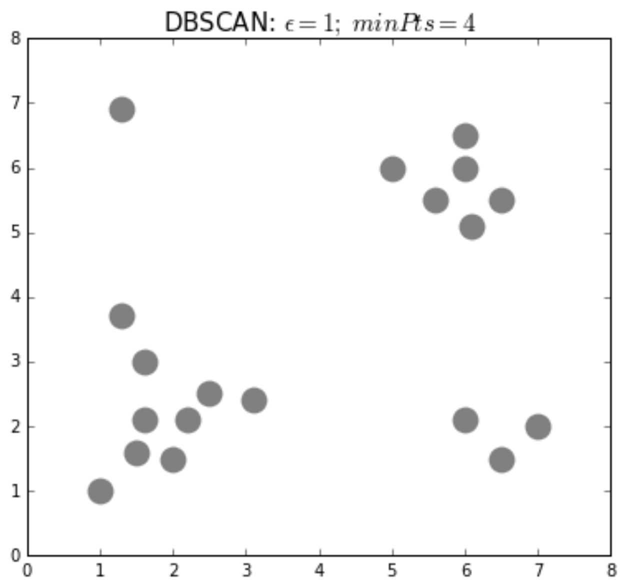
CLUSTERING: DBSCAN

Density-**b**ased **s**patial **c**lustering of **a**pplications with **n**oise

$\epsilon \equiv$ eps

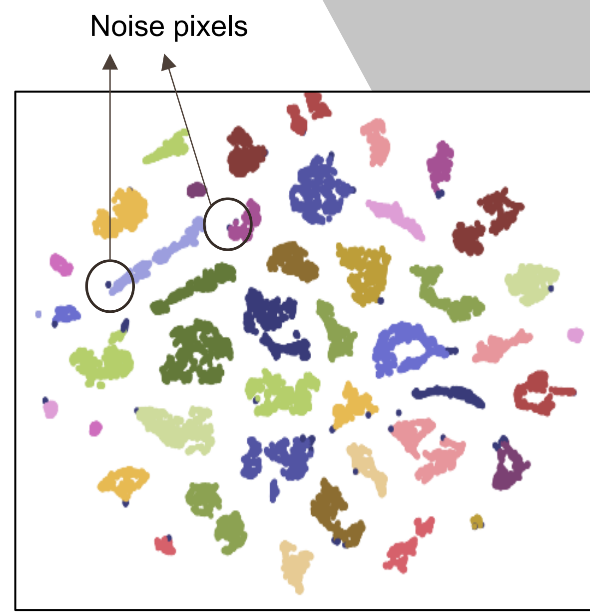


Embedded space:
Reduced dimensions with TSNE



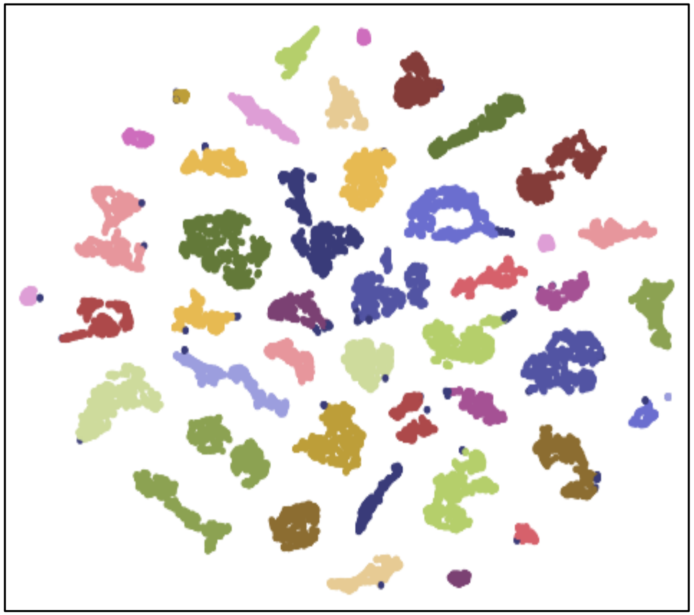
Sample DBSCAN algorithm

Ester[9]
GIF source: [10]

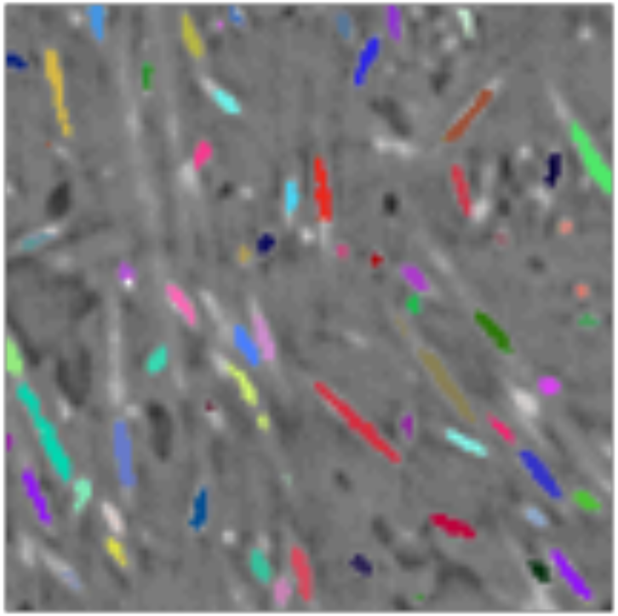


Clustered points.
Each color represents an instances

SAMPLE RESULTS

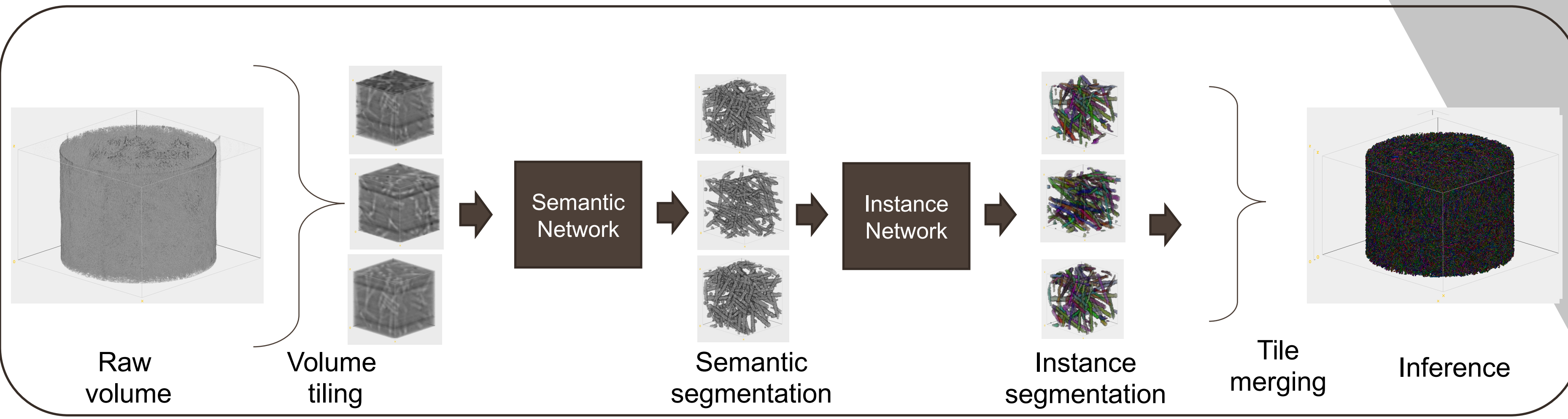


Embedded space
2D with TSNE



Volume space

VOLUME TILING AND MERGING



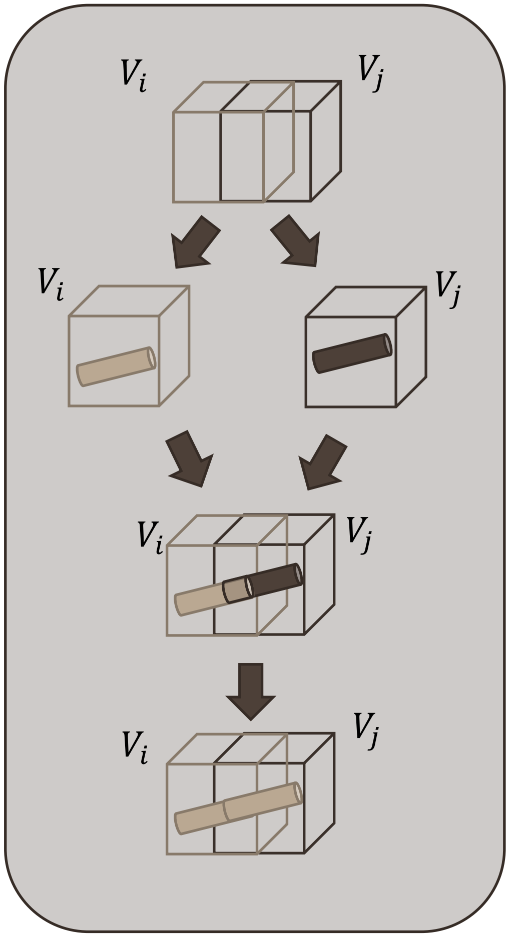
TILE MERGING

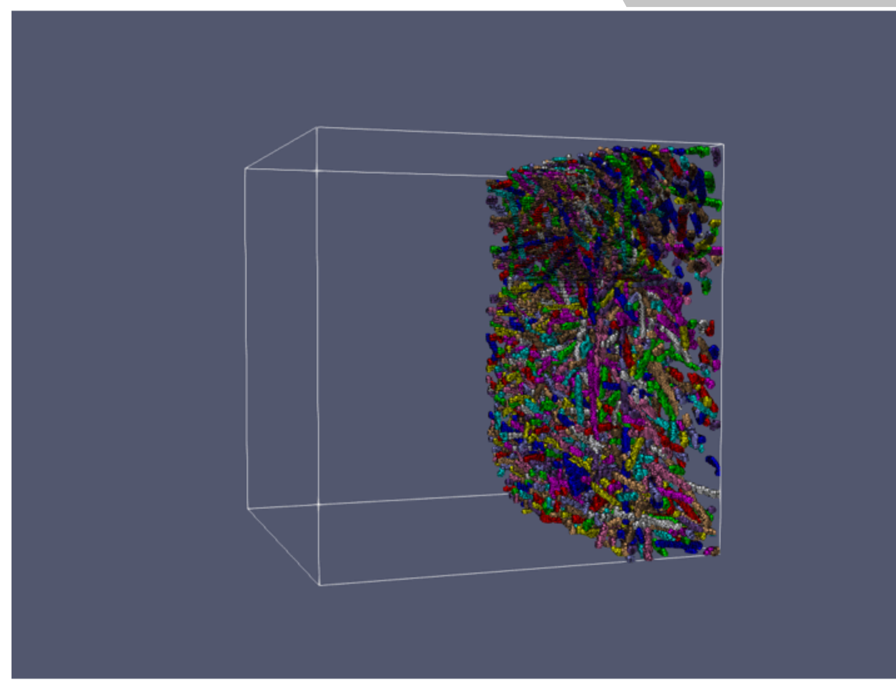
Overlapping tiles

Tile inference

Overlapping inferences

Fiber merging

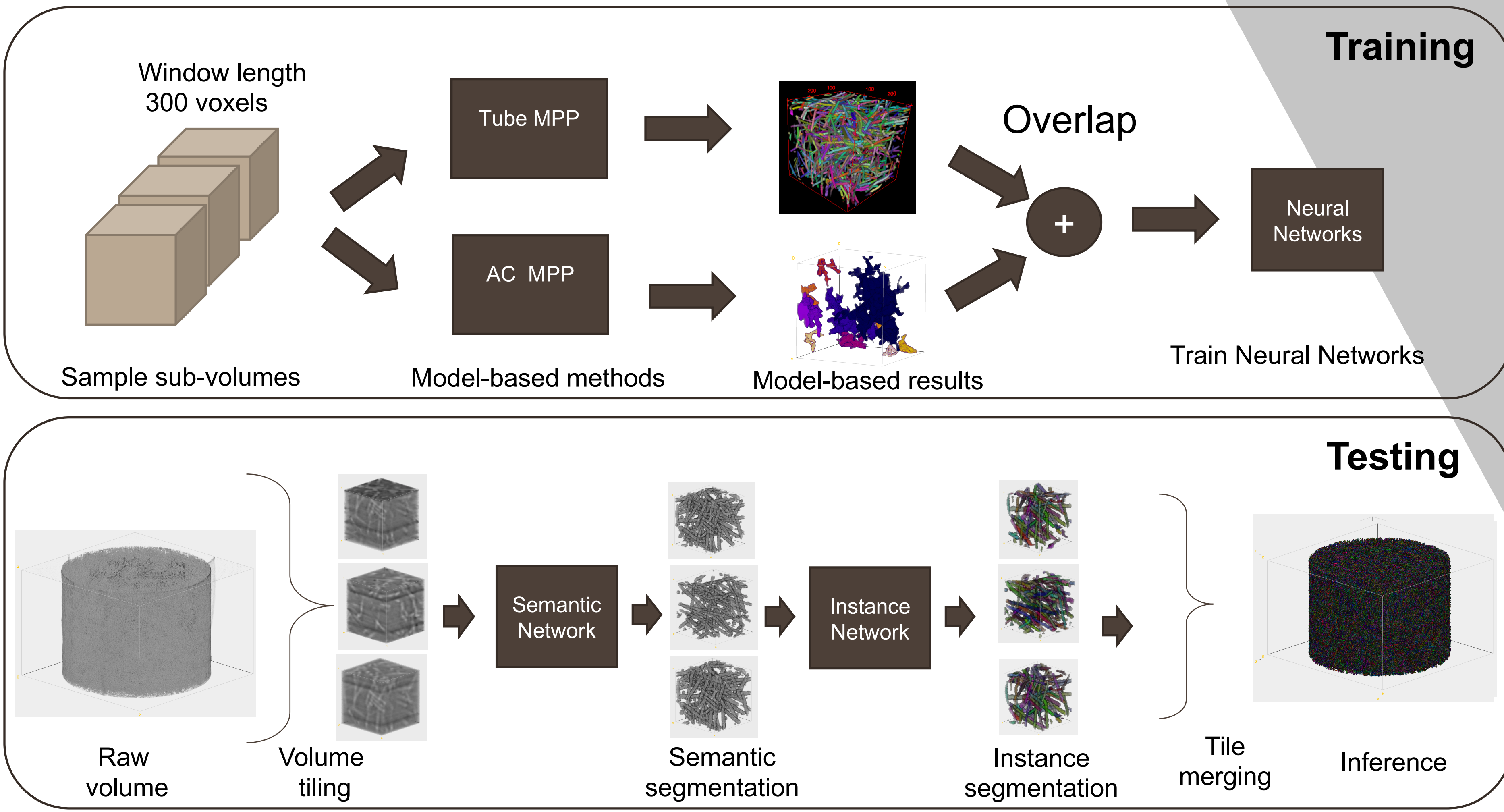




Sample Merging

Overlapping ratio: 50% of window length

PROPOSED SURROGATE METHOD:



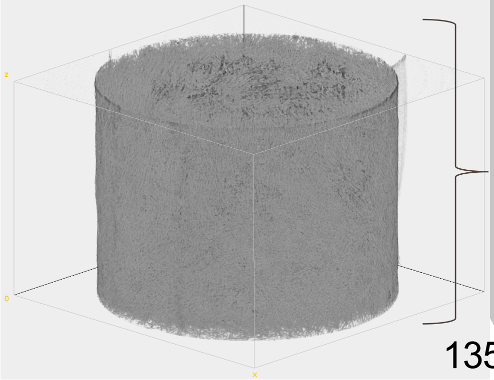
TIME COMPARISON

Model Based: Marked Point Process

Window Size	Voxels	MPP Fibers	MPP Voids
140 micron	300x300x300	18 mins	3 mins
700 micron	500x500x500	6 hours	20 mins
1900 micron	2500x2500x1300	*19 days	*26 days

CNN: Instance embedding learning

Window Size	Voxels	Training Semantic	Training Instance	Testing Semantic	Testing Instance
140 micron	300x300x300	1 hour	2 days	< 1 minute	2 mins
700 micron	500x500x500	1 hour	2 days	2 mins	48 mins
1900 micron	2500x2500x1300	1 hour	2 days	26 minutes	19 hours



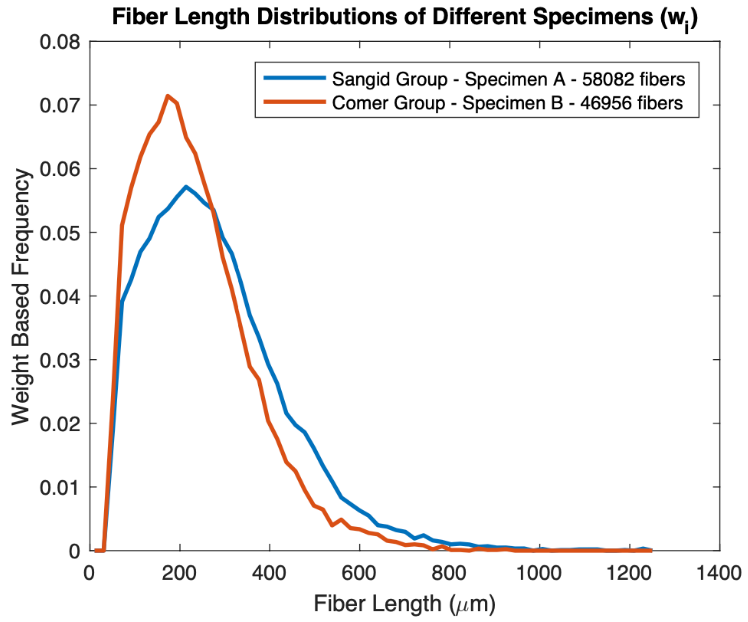
1350 voxels

2025x2025 voxels

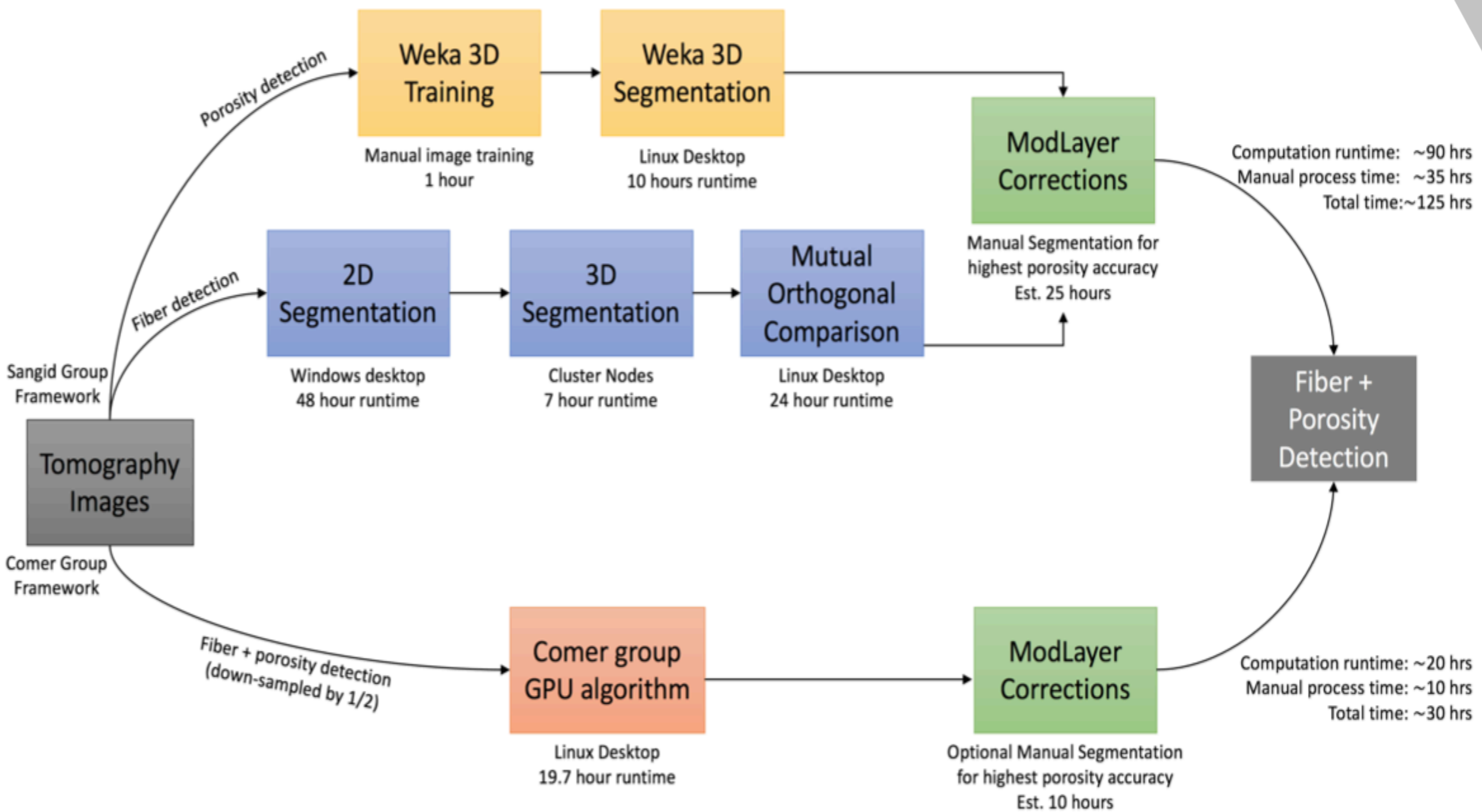
*Estimated times

VALIDATION WITH STATISTICS

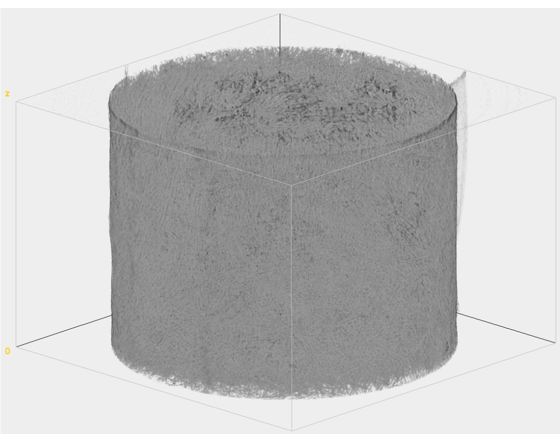
Property	Sangid Group	Comer Group
Fiber volume fraction	9.47 %	9.21%
Void volume fraction	3.63 %	2.78%
Number of fibers	4613	4045
Fibers with aspect ratio > 5	2108 45.70%	1858 fibers 45.96%



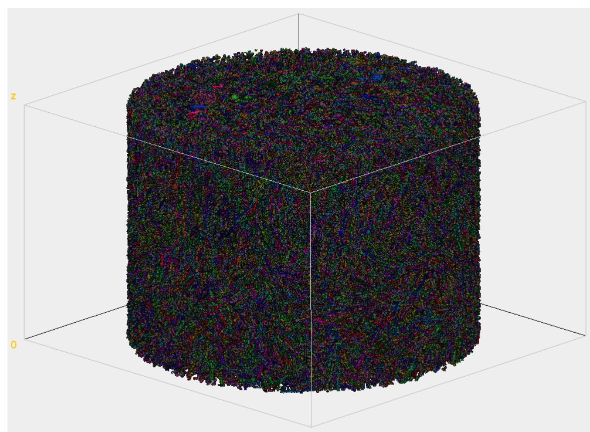
COMPARISON OF APPROACHES



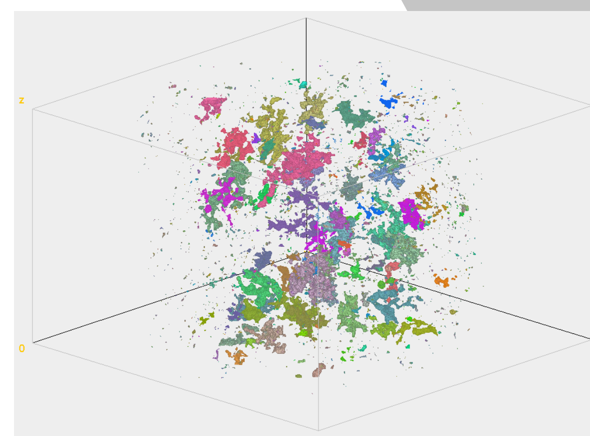
FINAL RESULTS



Reconstructed volume

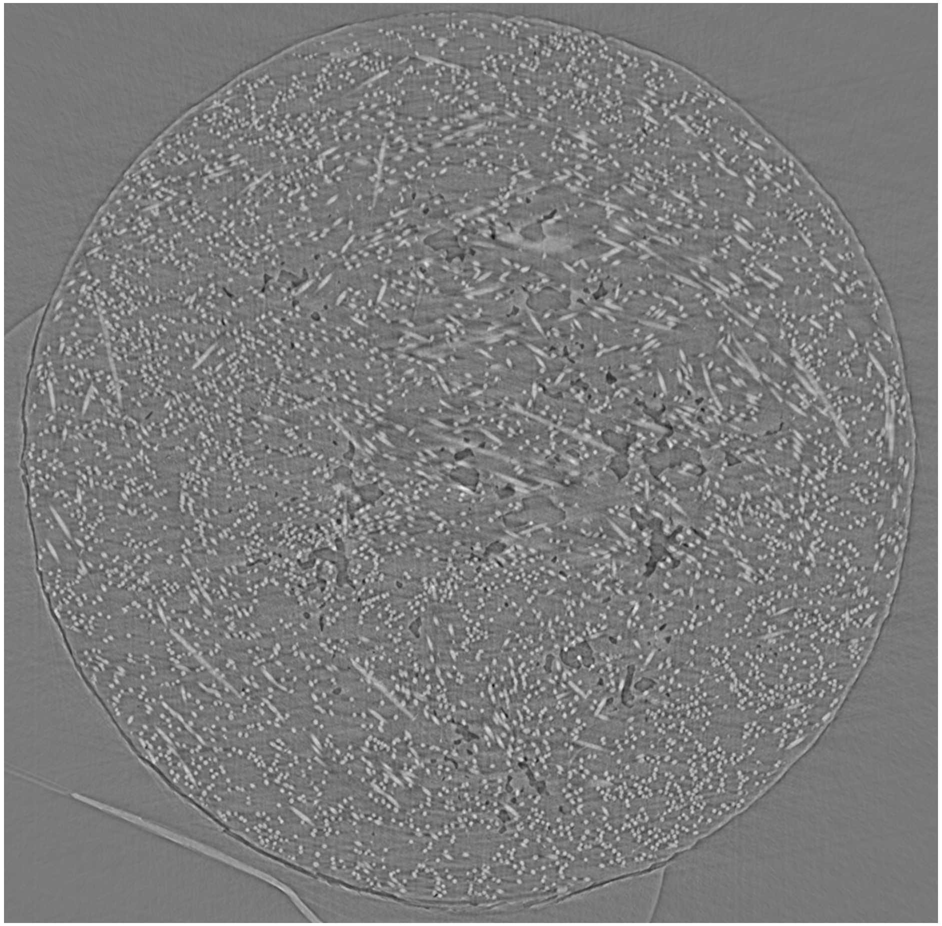


Fiber detection

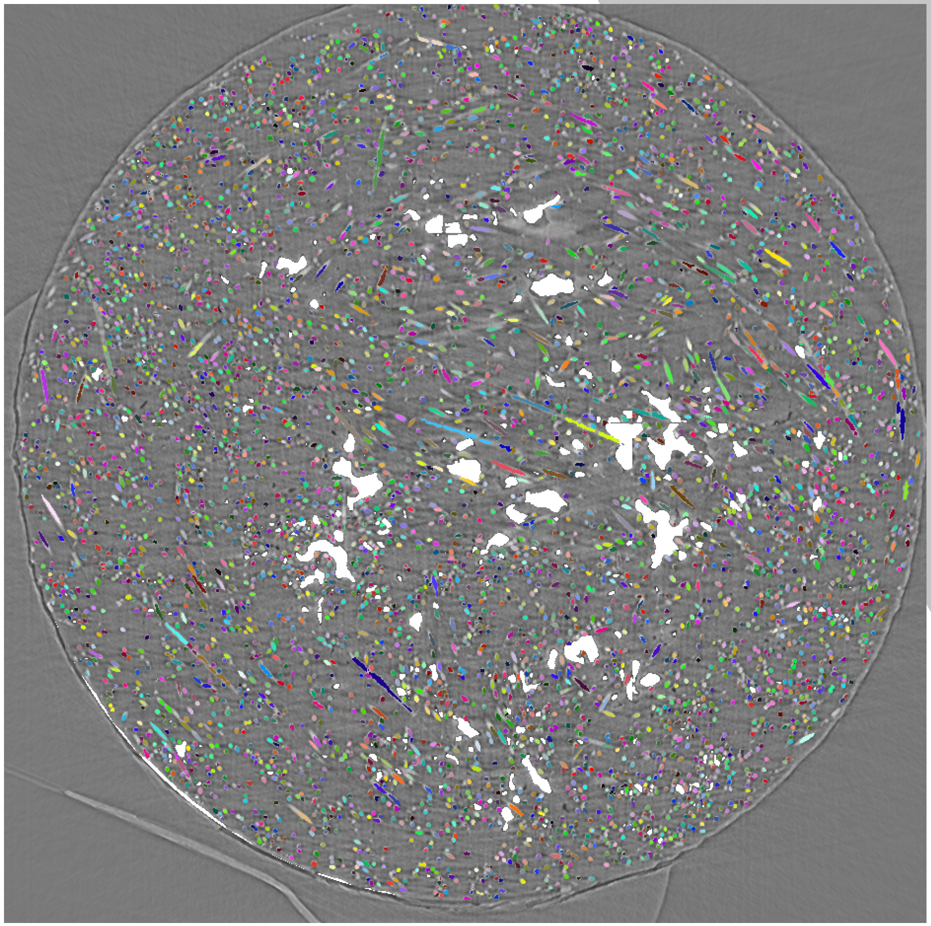


Void detection

SAMPLE VIEWS

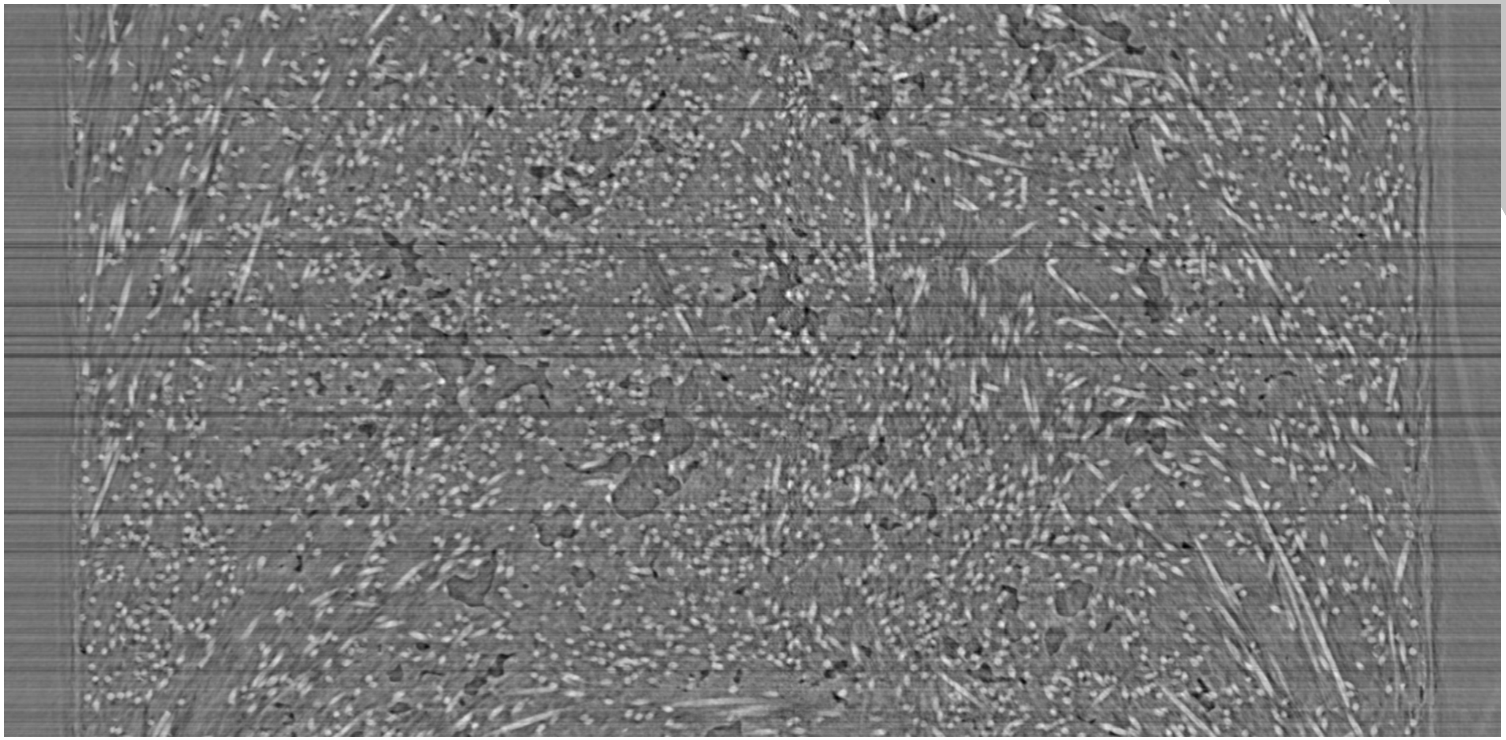


Original Image



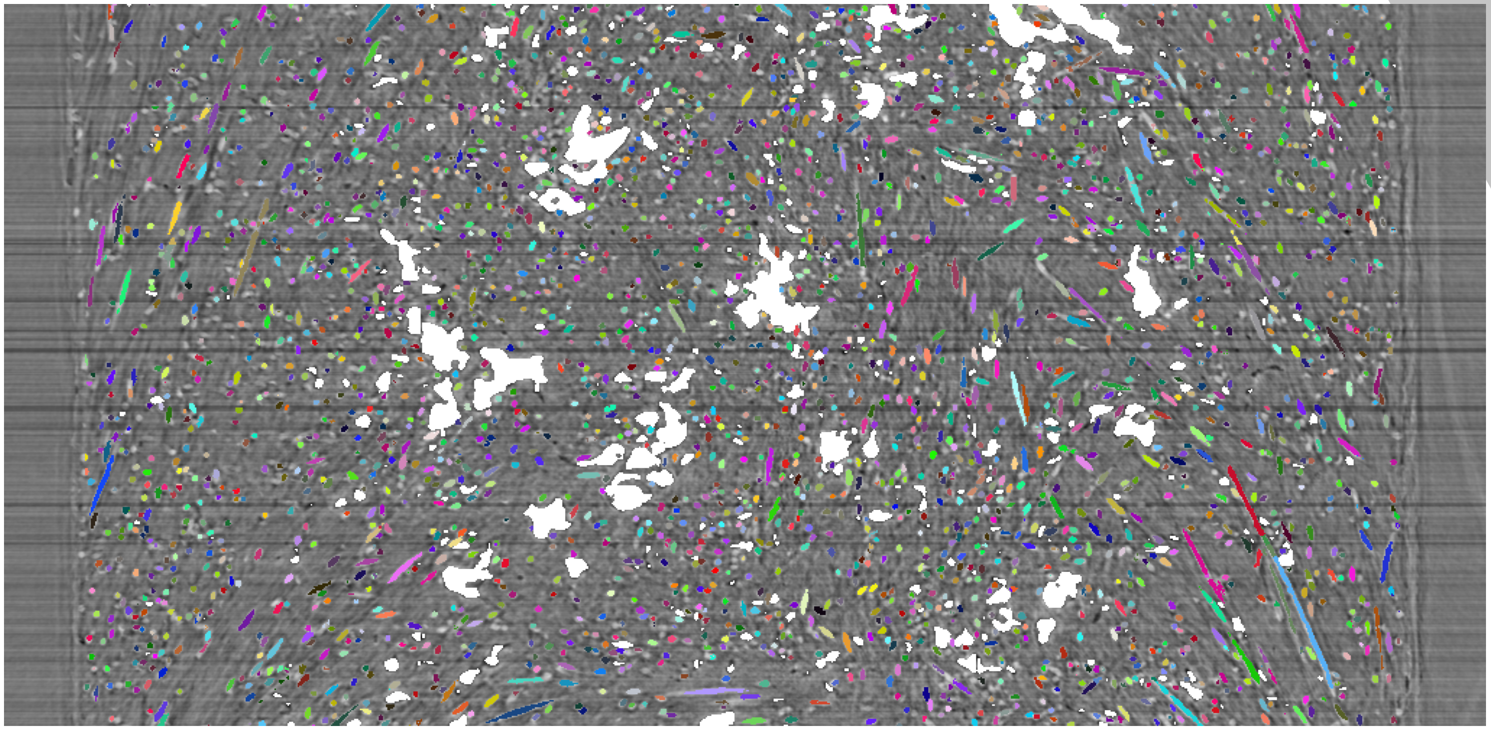
CNN Outputs

SAMPLE VIEWS



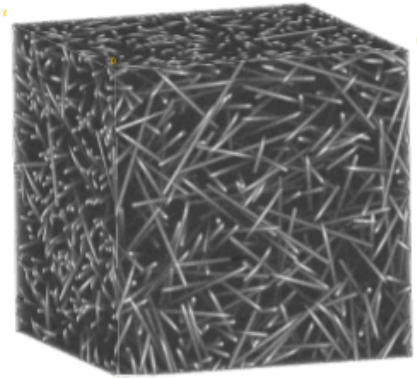
Original Image

SAMPLE VIEWS

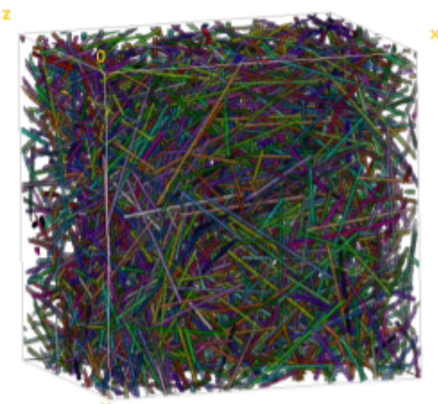


CNN Output

TESTING DATASET: SYNTHETIC DATASET



Sample volume

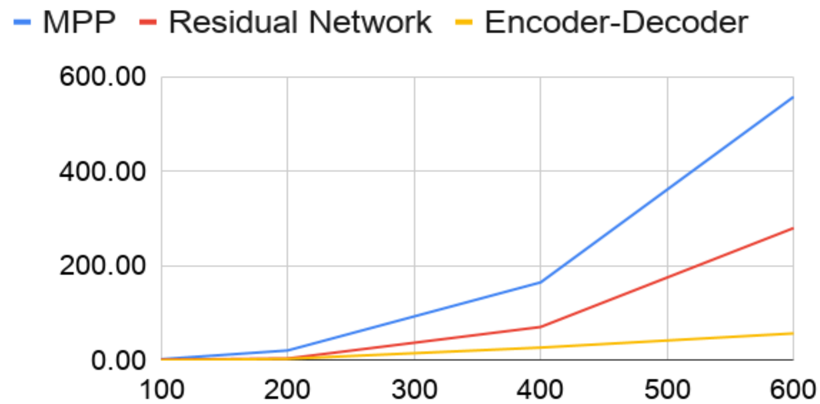


Labeled volume

Method	f1 score
MPP	**0.932**
R-Net	0.855
Proposed-trained with MPP	0.880
Proposed-trained with labels	0.930

Detection comparison

Inference time [minutes]



Volume size[voxels]

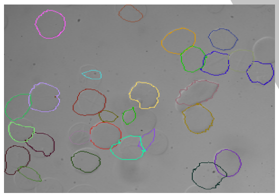
Dataset obtained from: Konopczyński[3]

CONCLUSION OF THIS APPROACH

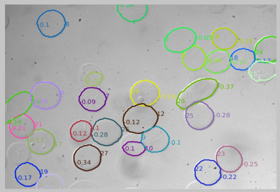
- We proposed a unified fiber-void segmentation with an encoder-decoder architecture
  - x20 memory efficiency over other architectures
- We obtained:
  - x24 time gain for detecting fibers over model-based
  - x32 time gain for detecting voids over model-based
  - x4.5 time gain over Sangid’s group approach
- Verified fiber and void statistics

OVERVIEW

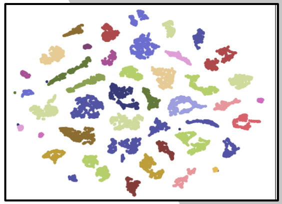
- **Introduction**
  - Problem statement
  - Preliminary work
- **Void and Fiber Segmentation Using Deep Learning**
  - Voids: 3D semantic segmentation
  - Fibers: 3D embedded learning
- **3D Fiber Detection using centroid regression**
  - Center regression
  - 3D object proposals
- **Summary**
  - Thesis contributions
  - Published works



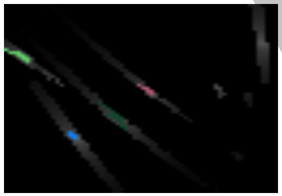
MPP + AC



MPP + LS



Embedded learning

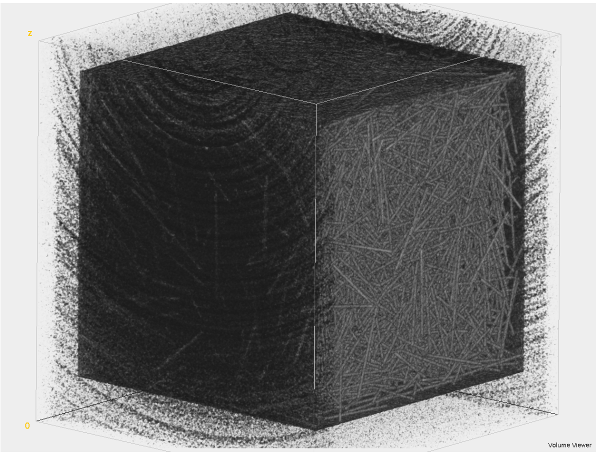


Center regression

Datasets obtained from: **Konopczyński[3]
**Hanhan[11]

FIBER DATASETS

Synthetic dataset*

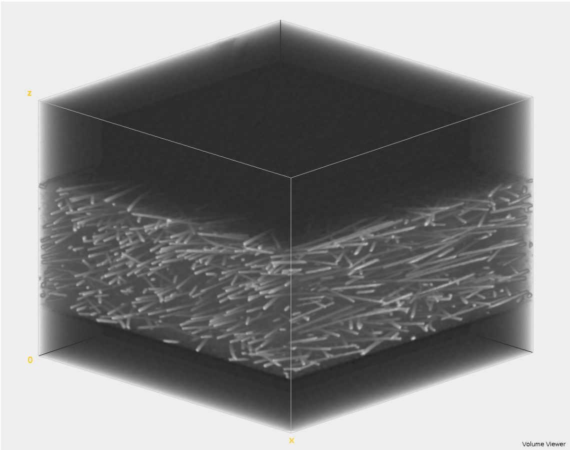


- Size = 586 × 584 × 627
- Resolution = 3.2 μm
- **True labels**

- Fiber r = 6.5 μm
- Fiber length = 500 μm

Low-resolution dataset*

Polybutylene terephthalate **PBT** reinforced with short glass fibers

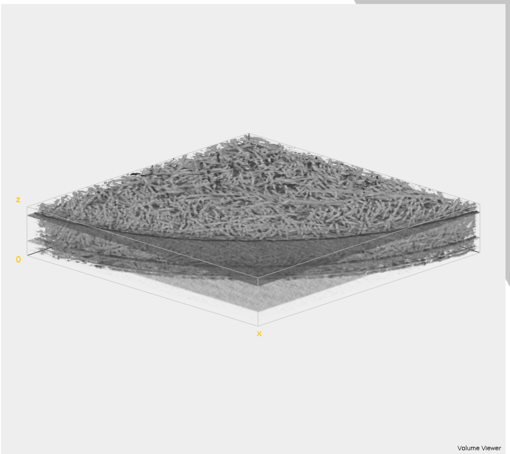


- Size = 200 × 200 × 260
- Resolution = 3.9 μm
- **Labels from watershed**

- Fiber r = 10 μm
- Fiber length = 500 μm

High-resolution dataset**

Polypropylene matrix reinforced with short glass fibers



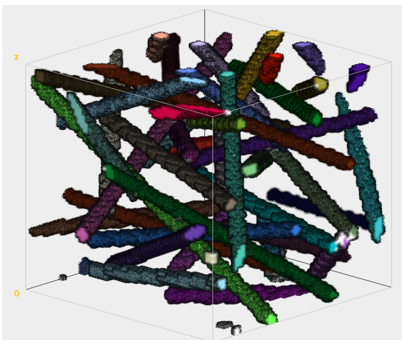
- Size = 950 × 950 × 150
- Resolution = 2.4 μm
- **Labels from Agyei[13]**

- Fiber r = 5 μm
- Fiber length = 200 μm

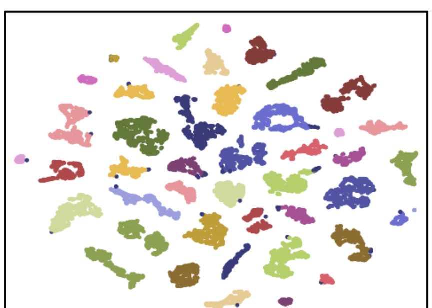
DRAWBACKS OF EMBEDDING LEARNING

- Embedding does not have a physical meaning

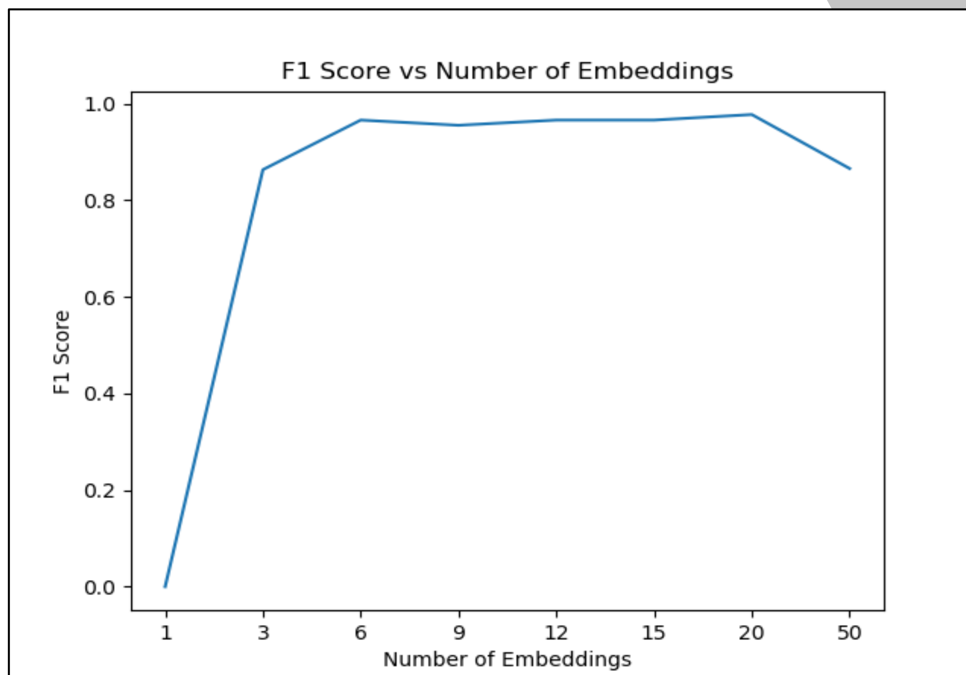
Synthetic Dataset



Volume inference



Embedded inference

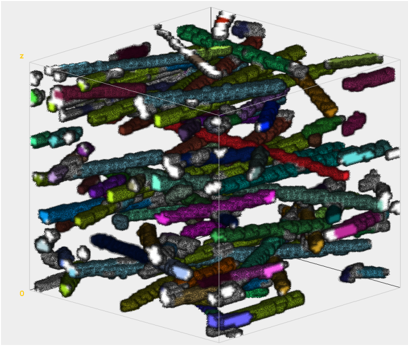


f1 score vs embeddings

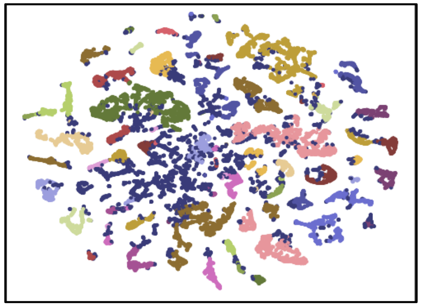
DRAWBACKS OF EMBEDDING LEARNING

- Embedding does not have a physical meaning

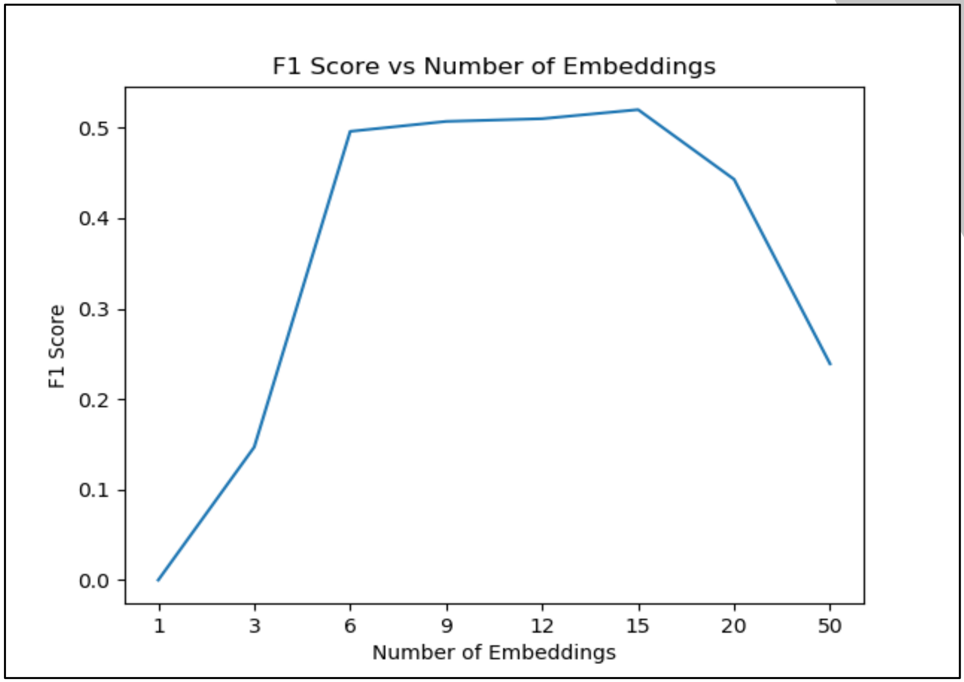
Low Resolution Dataset



Volume inference



Embedded inference



f1 score vs embeddings

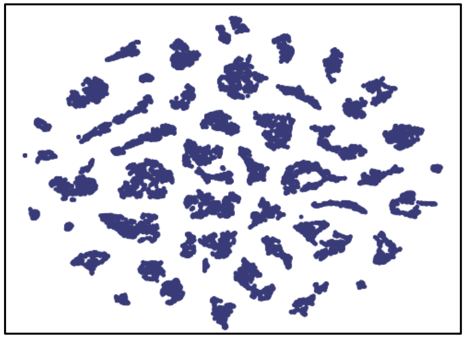
DRAWBACKS OF EMBEDDED LEARNING

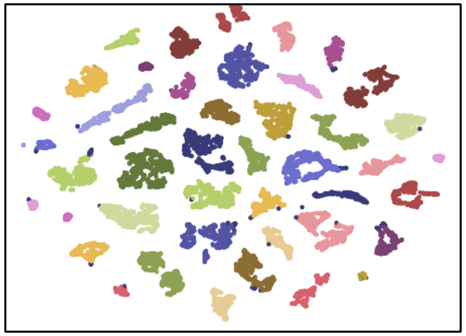
- Sensitivity to ϵ(eps) parameter

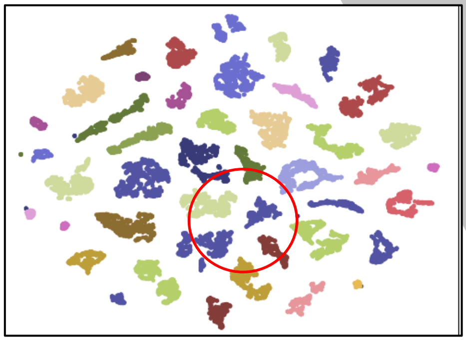
Synthetic Dataset

All points noise

Merged clusters



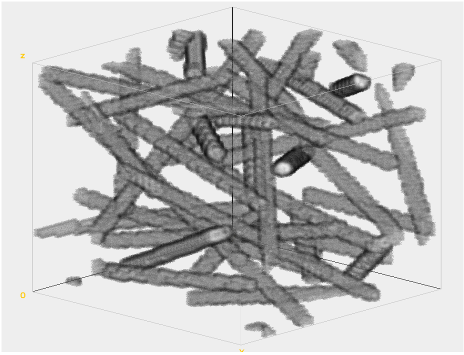


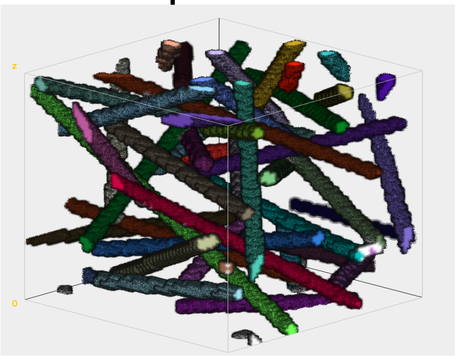


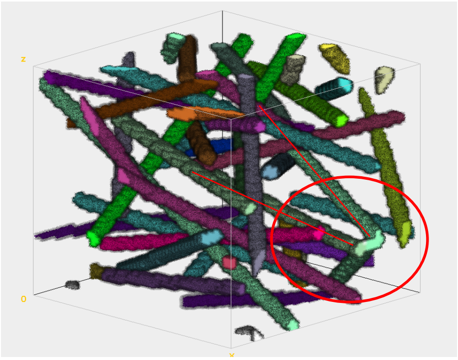
eps=0.1

eps=0.4

eps=1.2







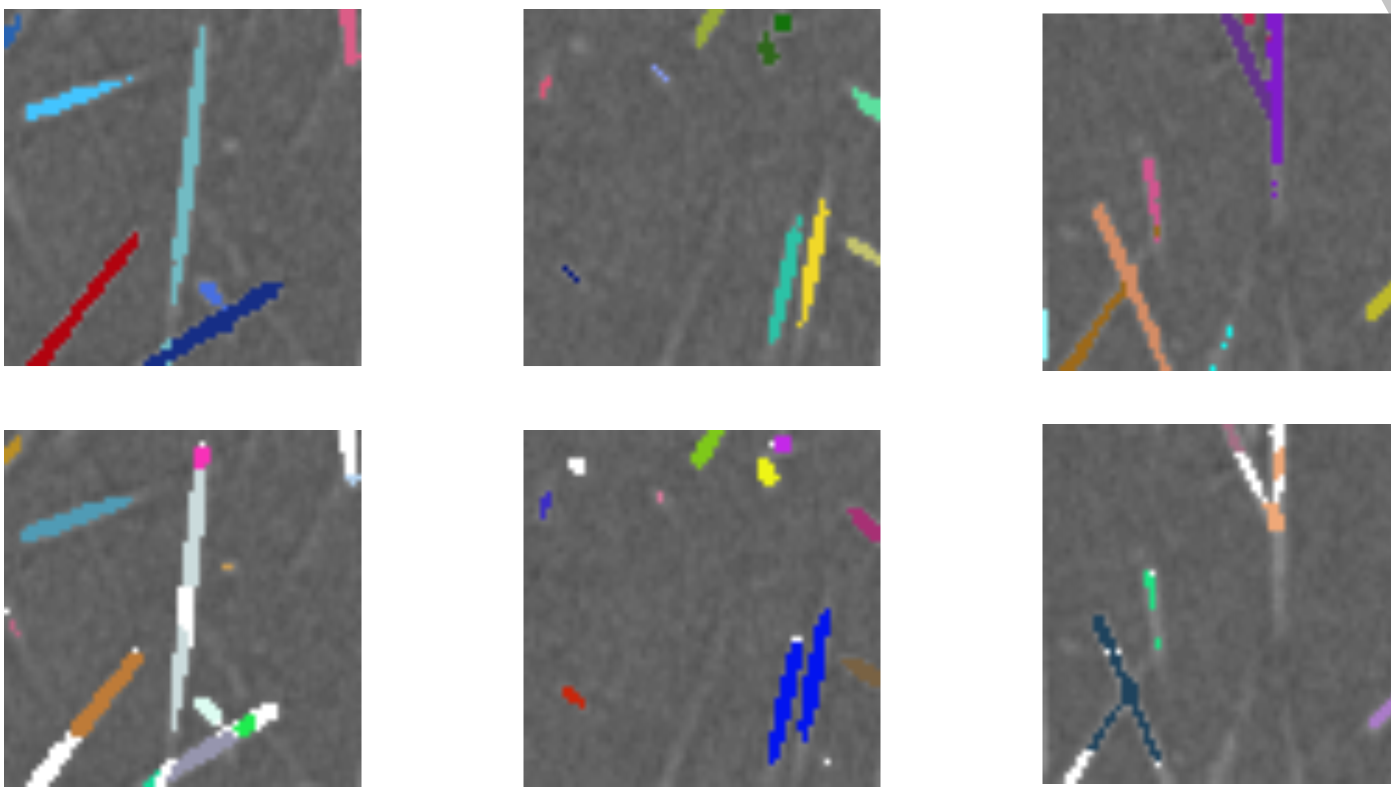
All fibers noise

Merged fibers

DRAWBACKS OF EMBEDDED LEARNING: SHAPE INDEPENDENT CLUSTERS

Labeled Images

Inference



Broken fibers | Merged parallel fibers | Merged perpendicular fibers

CENTER REGRESSION

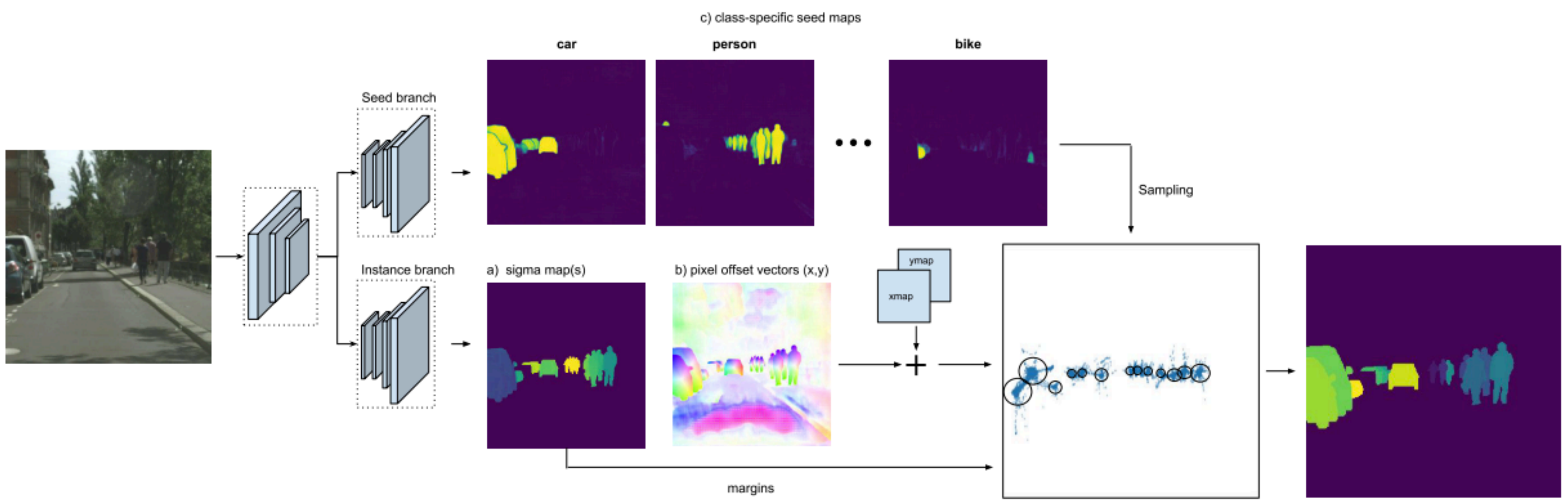
Objective:

-Generalize fiber detection for other datasets

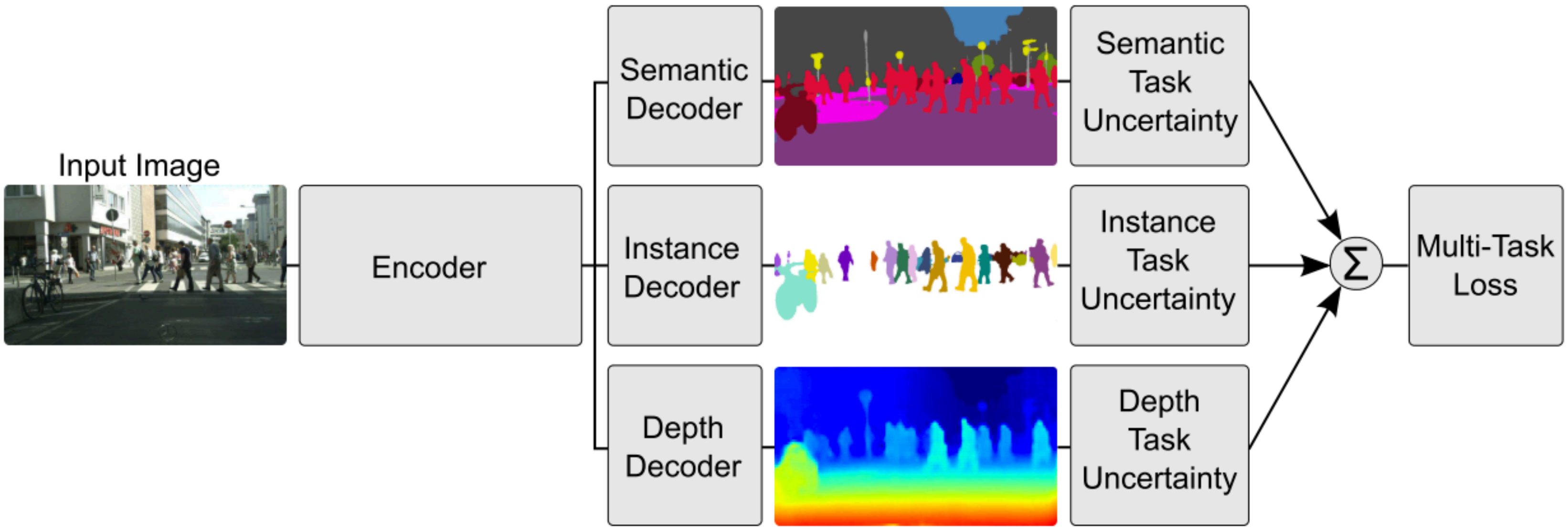
-Relate clustering parameter to physical properties

-Regularize clustering

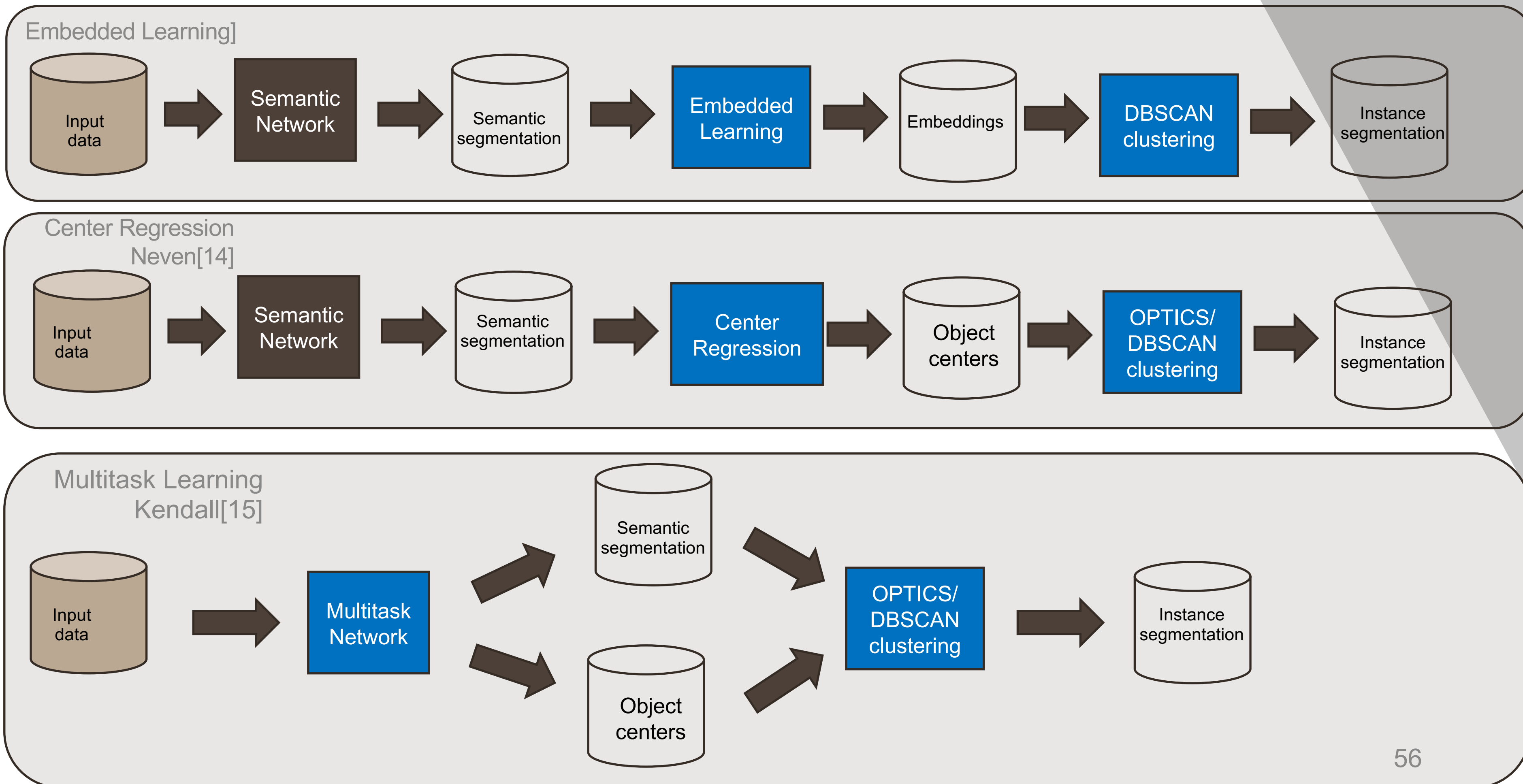
RELATED WORKS: CENTER REGRESSION [14] (NEVEN)



RELATED WORKS: MULTITASK LEARNING[15] (KENDALL)

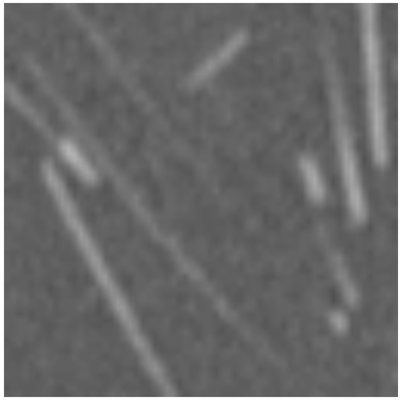


CLUSTERING-BASED SEGMENTATION METHODS

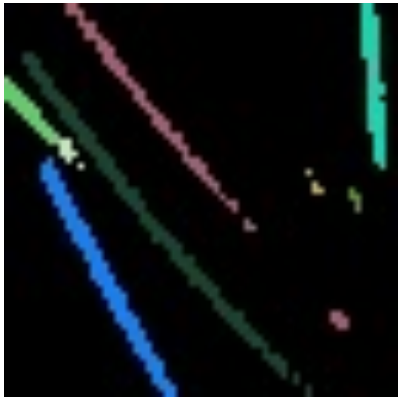


CENTER REGRESSION:

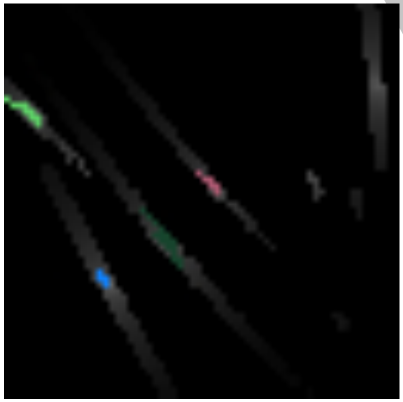
$$l_{center} = \frac{1}{C}\sum_{c=1}^{C}\sum_{o_i \in S_c}\left(\|o_i - \mu_c\|_2^2 - \delta_v\right)_+$$



Raw volume



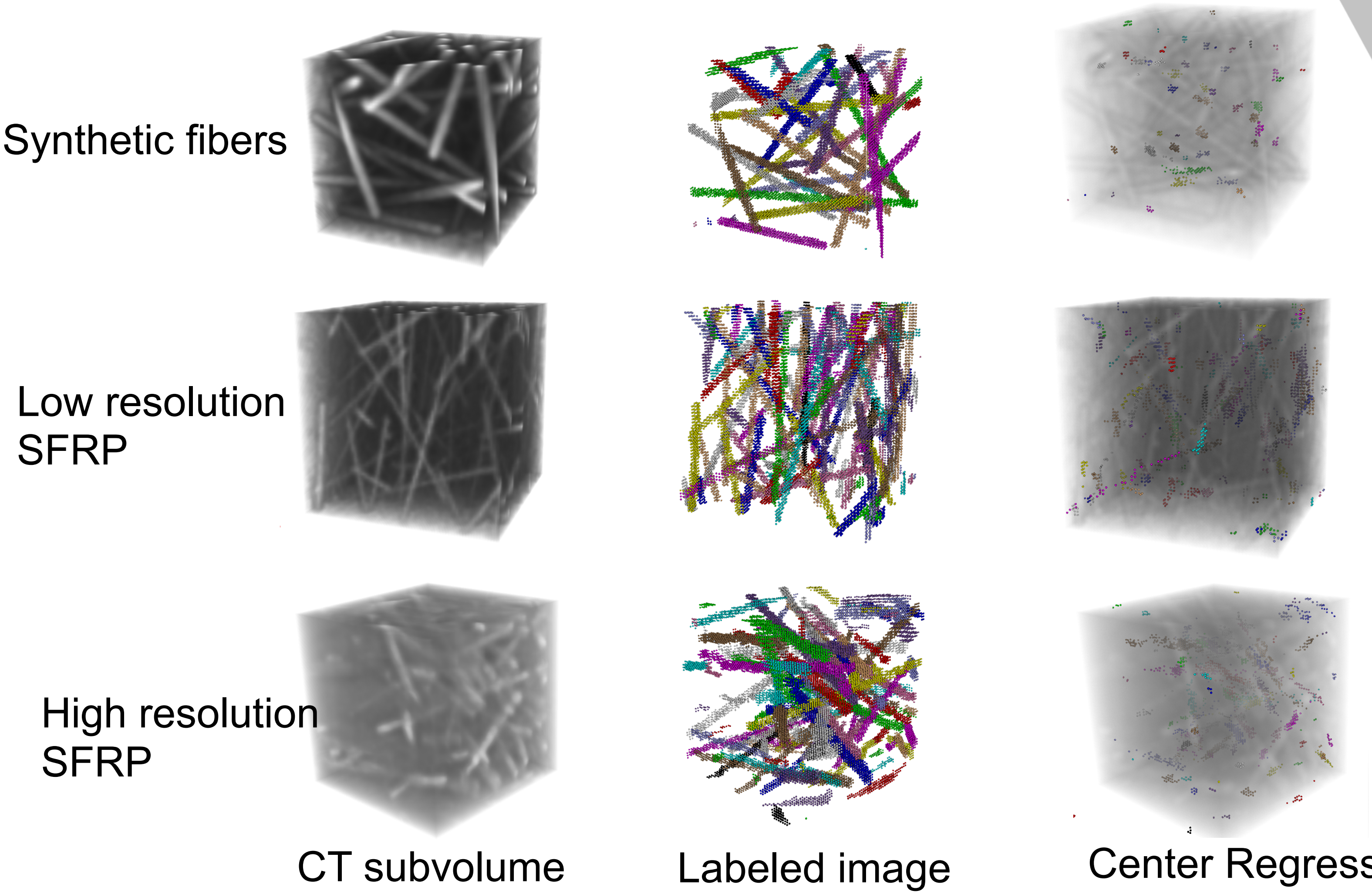
Labeled image



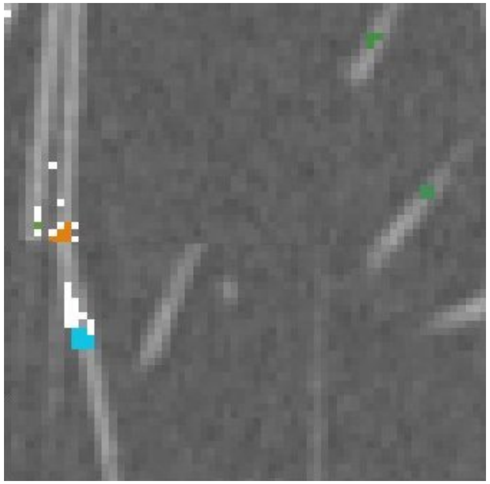
Center regression

C: Number of instances/clusters
μ_c: c^{th} fiber center
S_c: Set of voxels representing instance c
o_i: i^{th} center voxel output
$(a)_+ = \max(a, 0)$

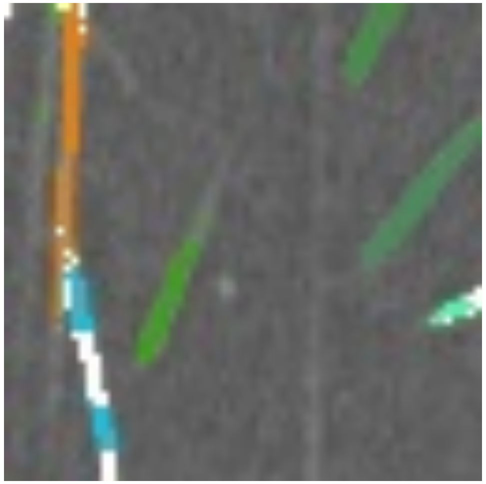
CENTER REGRESSION ACROSS OTHER DATASETS:



DBSCAN STILL PRESENTS DIFFICULTIES

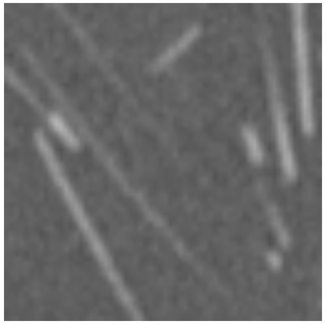


Center Regressed Pixels



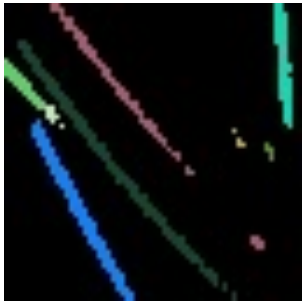
Segmentation

GEOMETRIC CLUSTERING

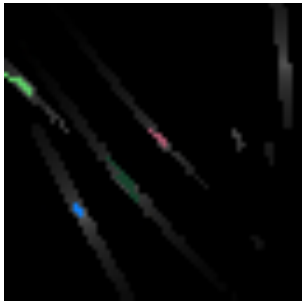


Sample image

Birthmap computation

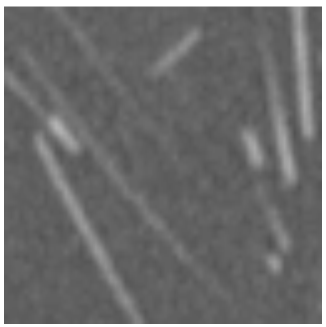


Labeled Image



Labeled regressed pixels

GEOMETRIC CLUSTERING



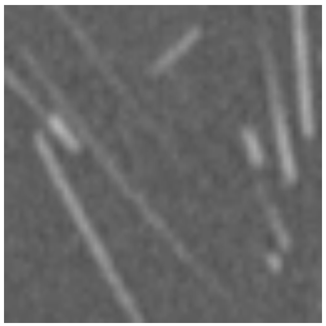
Sample image

Birthmap computation

Labeled Image

Labeled regressed pixels

GEOMETRIC CLUSTERING

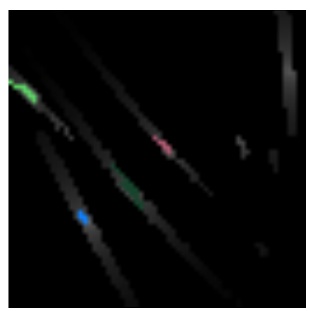


Sample image

Birthmap computation

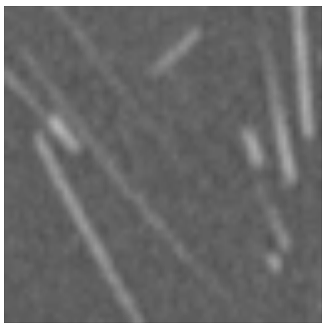
Cluster proposal

Labeled Image



Labeled regressed pixels

GEOMETRIC CLUSTERING



Sample image

Birthmap computation

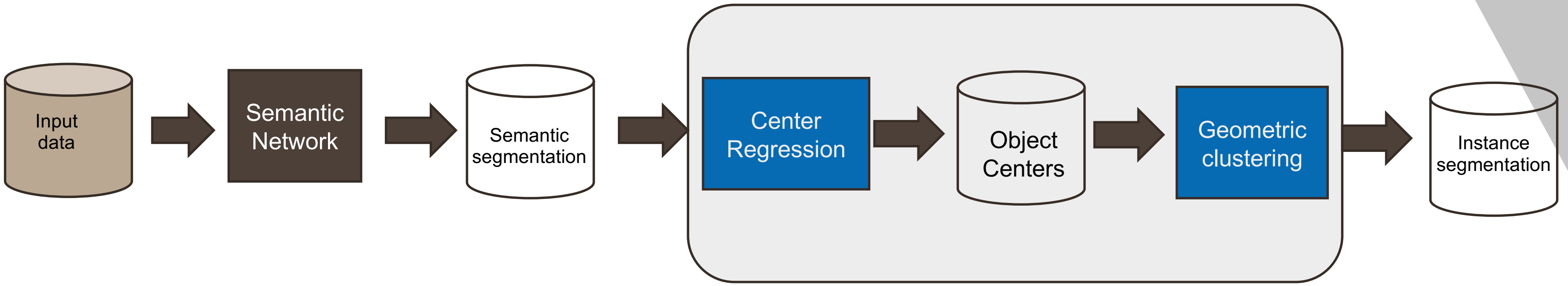
Cluster proposal

Labeled Image

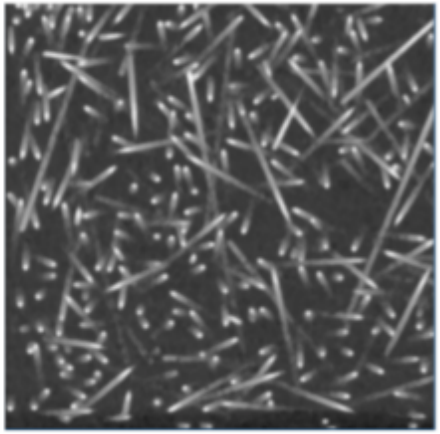
Labeled regressed pixels

Inference

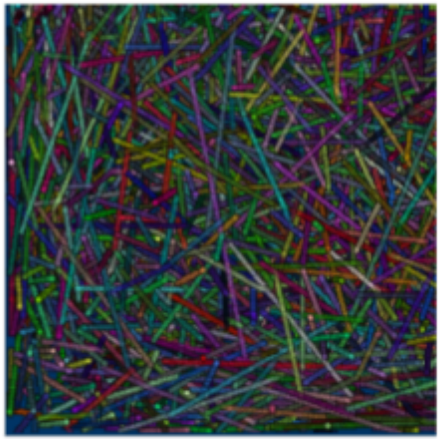
PROPOSED: CENTER REGRESSION + GEOMETRIC CLUSTERING



SYNTHETIC DATASET - TEST DATA



Raw volume

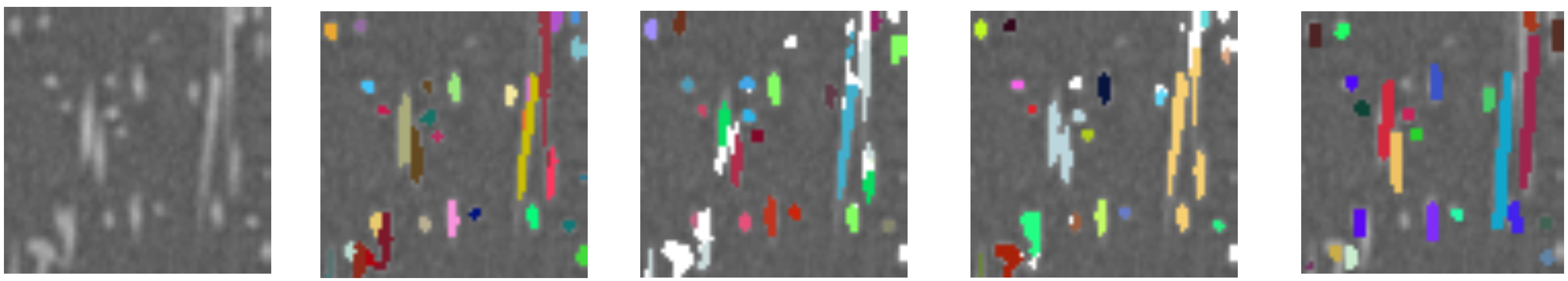


Segmentation

Method	f1
Embedded learning	0.983
Multitask learning	0.977
Centroid regression + DBSCAN	0.993
Centroid regression + geometric clustering	0.973

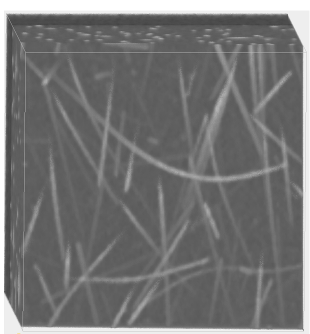
RESULTS
LOW RESOLUTION SFRP

Method	f1
Embedded learning and DBSCAN	0.634
Multitask learning	0.831
Centroid regression and DBSCAN	0.832
Proposed	0.917



Cross section

White: noise pixels



Raw volume

Labels

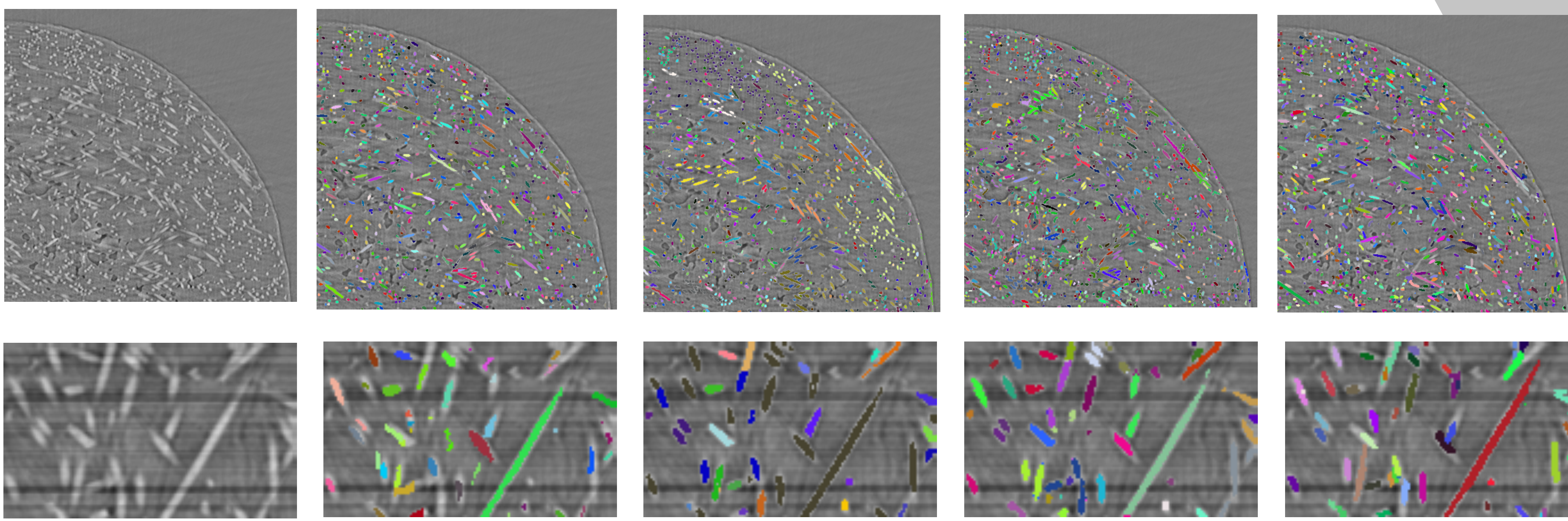
Multi-Task

Center regression only

Proposed

RESULTS
HIGH RESOLUTION SFRP

Method	f1
Embedded learning and DBSCAN	0.604
Multitask learning	0.733
Centroid regression and DBSCAN	0.767
Proposed	0.855

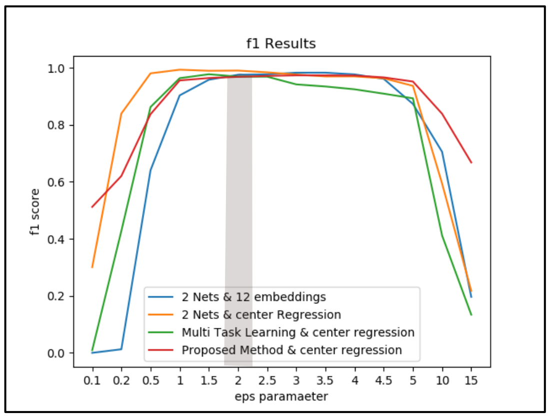


Raw volume | Labels | Multi-Task | Center regression only | Proposed

RESULTS VS EPS PARAMETER

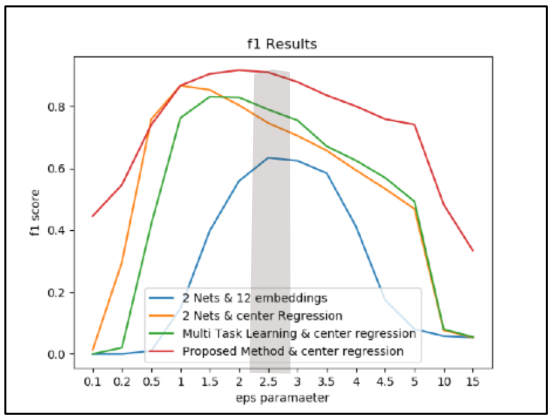
f1

Synthetic Fibers



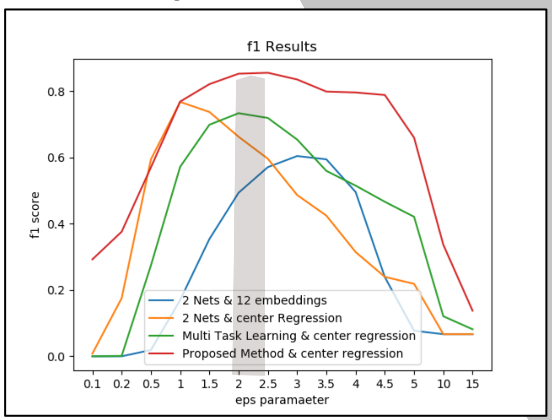
Mean fiber $\hat{r}$ = 2.03 pixels

Low Res Fibers



Mean fiber $\hat{r}$ = 2.56 pixels

High resolution fibers



Mean fiber $\hat{r}$ = 2.08 pixels

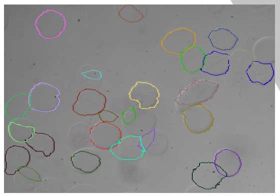
*eps parameter for embedded learning has a different scale

CONCLUSION OF THIS APPROACH

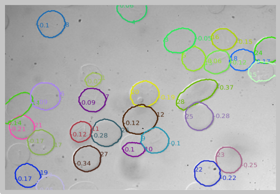
- Our approach shows robustness across several datasets thanks to the center regression
- The geometric clustering allows to constraint the segmentation with prior image knowledge (cylindrical objects)
- The ϵ parameter has a physical relation to the fiber objects

OVERVIEW

- **Introduction**
  - Problem statement
  - Preliminary work

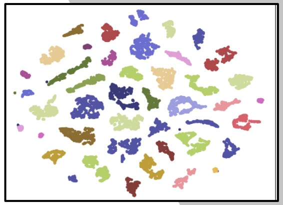


MPP + AC



MPP + LS

- **Void and Fiber Segmentation Using Deep Learning**
  - Voids: 3D semantic segmentation
  - Fibers: 3D embedded learning



Embedded learning

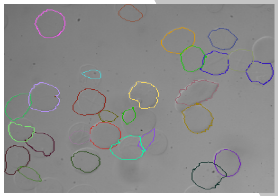
- **3D Fiber Detection using centroid regression**
  - Center regression
  - 3D object proposals

Center regression

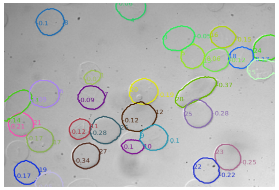
- **Summary**
  - Thesis contributions
  - Published works

CONTRIBUTIONS OF THIS THESIS

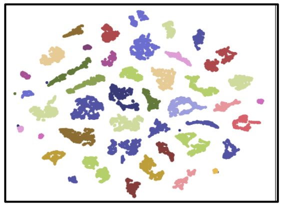
- Model Based:
  - MPP + active contours
  - MPP + level sets
- Deep Learning:
  - 3D embedded segmentation
  - 3D regression + geometric clustering



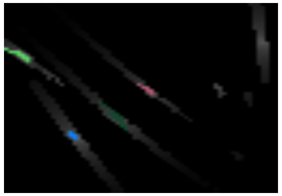
MPP + AC



MPP + LS



Embedded learning



Center regression

PUBLICATIONS OF THIS THESIS

- **C. Aguilar** and M. Comer, "A Marked Point Process Model Incorporating Active Contours Boundary Energy," Electronic Imaging, vol. 2018, no. 15.
- **C. Aguilar** and M. Comer, "Void detection and fiber extraction for statistical characterization of fiber-reinforced polymers," Electronic Imaging, vol. 2020, no. 23.
- ***C. Aguilar** and M. Comer, "Segmentation and Detection of Irregularly-Shaped Regions Using Integrated Marked Point Processes and Level Sets," in IEEE Transactions on Image Processing to be submitted July 2020.
- ***C. Aguilar** and M. Comer, "3D Fiber Segmentation with Deep Center Regression and Geometric Clustering," in IEEE Transactions on Image Processing. To be submitted July 2020.

ACKNOWLEDGEMENT

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THANK YOU