Robust Skeletonization for Plant Root Structure Reconstruction from MRI

ICPR 2020 Presentation

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Motivation

- Understanding of plant behavior necessitates understanding of plant roots
- Therefore root scans have to be transformed to root graphs
- Manual annotation is time consuming
- Not feasibly for available datasets
- Automated extraction would allow to process and use all data available
- Enhance the understanding of plant roots utilizing all raw data possible

Plant Root MRI Data and Goal

- Low resolution, low signal to noise ratio
- Upscaled and segmented using 3D U-Net. Zhao et al. [ZWL+20]
- Outputs still contain noise and disconnected roots

Goal: Extract a connected root graph despite gaps and noise

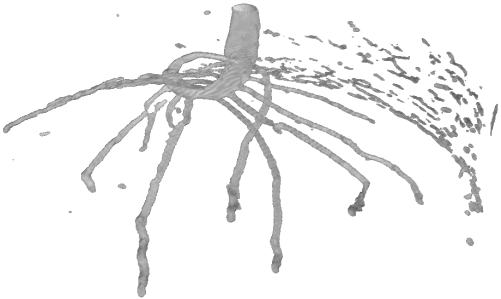
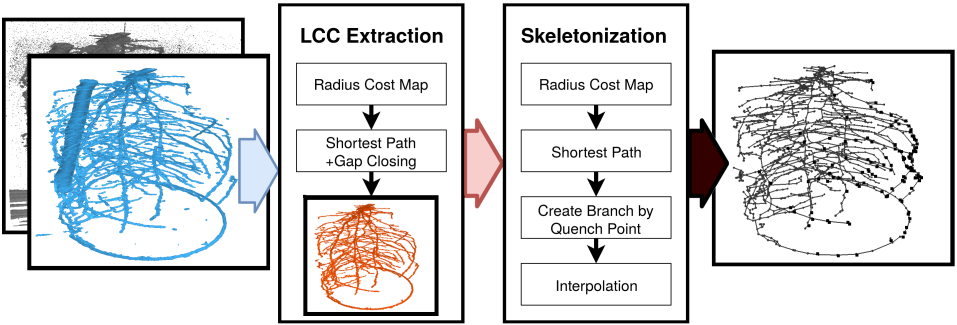


Figure: Segmented MRI input

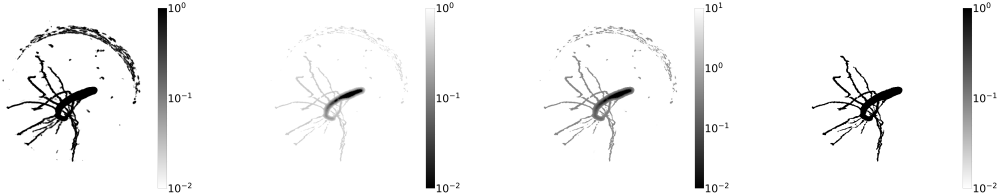
Plant Root Structure Reconstruction



Largest Connected Component Extraction

- Generate radius/intensity cost map
- Apply intensity mask for gap voxel
- Apply Dijkstra shortest path [Dij59]
- Find unique gap bridges of limited length
- Extract all voxel with small path cost

Figure: Extracted LCC



(a) Input (b) Radius Cost Map (c) Masked gap values (d) LCC

Curve Skeletonization

- Based on Jin et al. [JIC+16]
- Get radius map from LCC
- Apply Dijkstra to cost map
- Connect valid quench points by Eucl. distance
- Fill volume around extraction using dilated radius
- Suppress filled quench points

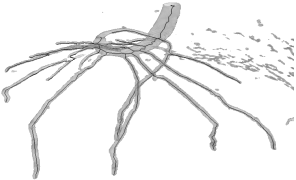
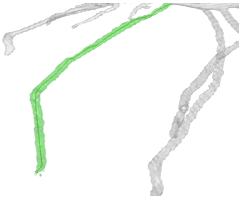


Figure: Extracted root graph

(a) Quench point

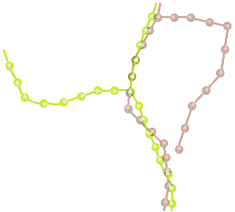
(b) Connection



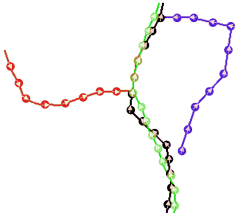
(c) Filled volume

F1 Score for Graphs

- Generate dense point clouds from extraction and target graphs
- Extract dense points and direction per line segment
- Establish correspondence between points in both graphs
- Correspondence necessitates close proximity and similar direction
- Calculate Recall and Precision score using point correspondence/no-correspondence



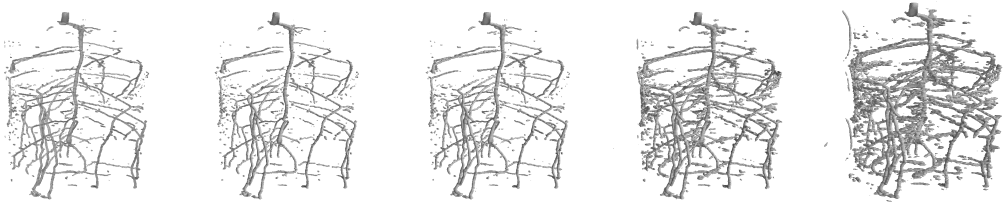
(a) Gray: Manual extraction, Yellow: Algorithmic extraction



(b) Black/Blue: Manual extraction with/without correspondence, Green/Red: Algorithmic extraction with/without correspondence

Dataset

- 22 real plant root MRI scans with human annotated target
- 5 types of 3D U-Net segmentation
- Trained using different loss modifications
- Loss retaining surface structure perform best (LOG1, rw10)
- Loss with high root weights enlarge and merge structures
- Low root weight increases gaps and looses small structures



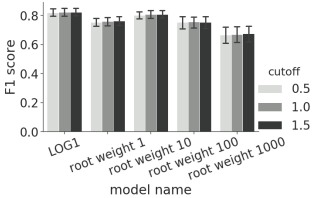
(a) LOG1 loss (b) root weight 1 (c) root weight 10 (d) root weight 100 (e) root weight 1000

Figure: Root scan segmented using differently trained U-Nets

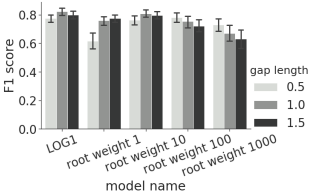
Performance based on Input and Parameters

Three parameters of the algorithm were tested:

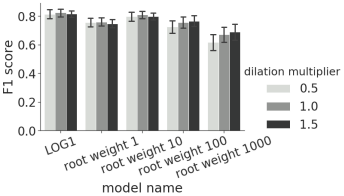
- Maximum cost for LCC extraction
- Maximum allowed gap length for LCC extraction
- Dilation multiplier used for volume filling



(a) Changing LCC path cost cutoff



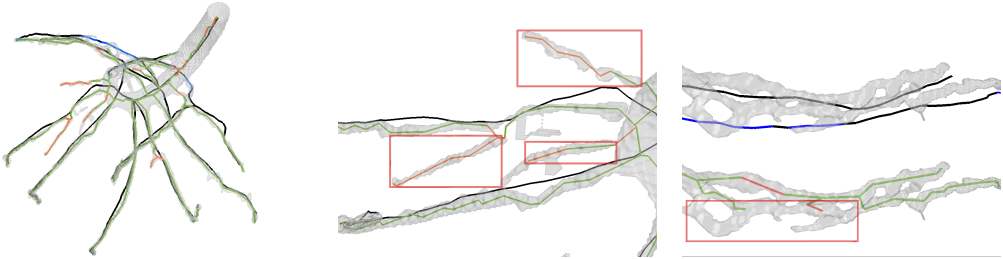
(b) Changing maximum gap length



(c) Changing dilation multiplier for skeletonization

Qualitative Assessment

- Roots are extracted using a unique response per branch
- Elongated root like structures not part of the target are extracted
- Merging volume leads to merging extraction
- Shortest path gap closing leads to artificial connections

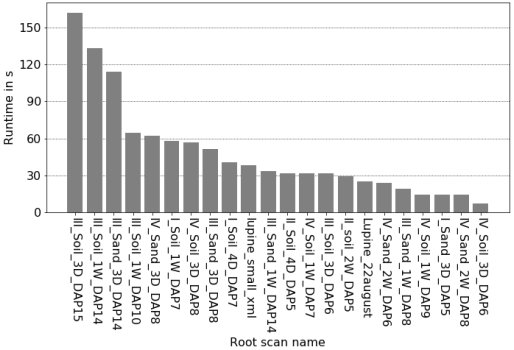


(a) Full extraction (b) Rootlike structure found (c) Merging structures

Figure: Black/Blue: Manual extraction, Green/Red: Algorithmic extraction

Runtime and Memory Usage

- Test computer: 8GB RAM, 2 Cores@2.3GHz
- Input volumes of size 140x512x512 to 396x512x512
- Avg Memory usage 4-6GB, max 10.8GB



Discussion

- We proposed a fast, robust pipeline to extract root graphs from 3D MRI scans
- Large datasets can be computed fast on modest hardware
- Possible root structures not part of the manual reconstruction were found
- Two areas to be improved were found:
  - Merging root structure can result in merging extraction
  - Shortest path gap closing can be inaccurate
- A dynamic model based on root growth could reduce both
- An iterative approach for extraction can be tried
- Use algorithm output as basis for manual improvements

Acknowledgment

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- Dakai Jin, Krishna S Iyer, Cheng Chen, Eric A Hoffman, and Punam K Saha, *A robust and efficient curve skeletonization algorithm for tree-like objects using minimum cost paths*, Pattern Recognition Letters **76** (2016), 32–40.
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