ROBUST SKELETONIZATION FOR PLANT ROOT STRUCTURE RECONSTRUCTION FROM MRI

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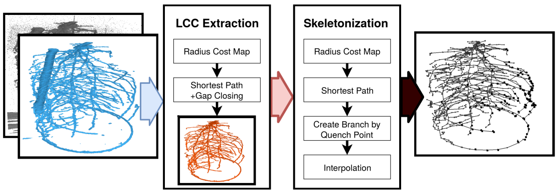
ABSTRACT

Structural reconstruction of plant roots from MRI is challenging, because of low resolution and low signal-to-noise ratio of the 3D measurements which may lead to disconnectivities and wrongly connected roots. We propose a two-stage approach for this task. The first stage is based on semantic root vs. soil segmentation and finds lowest-cost paths from any root voxel to the shoot. The second stage takes the largest fully connected component generated in the first stage and uses 3D skeletonization to extract a graph structure. We evaluate our method on 22 MRI scans and compare to human expert reconstructions.

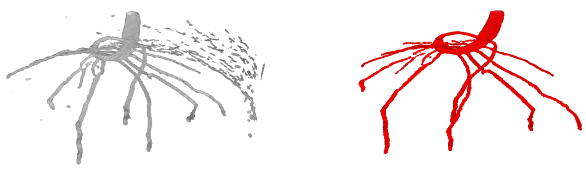
PIPELINE



INTRODUCTION

- Plant root system architecture is important for plant performance, particularly under challenging environmental conditions such as droughts
- 3D volumetric imaging methods enable in-situ observations of roots in opaque soil
- Root structure graphs must be extracted
- Currently done mostly manually by human experts
- Time consuming and not feasible for even available raw data
- MRI root scans can suffer from low resolution and SnR
- 3D UNet segmentation is used for preprocessing (Zhao et al., 2020)
- An algorithm to extract root structure graphs from root scans containing noise and disconnected structures is necessary

EXAMPLE THRESHOLDED INPUT AND LCC

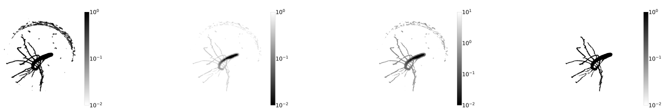


LARGEST CONNECTED COMPONENT EXTRACTION

To apply skeletonization a connected element is necessary. The LCC should exclude remaining noise and find and connect all root elements. Local radius estimates are used to filter noise. This is combined with the local intensity and inverted, generating a cost map. Disconnected root structures should be connected along a single unique path to the remaining root. Cost at positions above a cost threshold are increased further.

A starting point in the plant shoot is automatically found or given. Starting from this point the Dijkstra shortest path algorithm (Dijkstra, 1959) is applied. Should the shortest path to a low cost area traverse a limited high cost area, the assumption is made a gap was found. The path cost is modified to reflect the assumption root information is missing and the disconnected area is explored first now. All voxel of high intensity with valid path and all voxel needed to form these paths are include in the LCC.

SEGMENTATION, COST, GAP COST, LCC

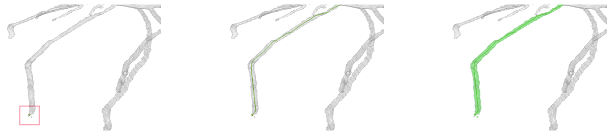


3D SKELETONIZATION

Based on Jin et al., 2016. First the local radius in the LCC is extracted. Local high points in the radius map are selected as quench points. These are then sorted by Euclidian distance to the start point. The inversed radius is used as cost map for another run of the Dijkstra shortest path algorithm.

Each quench point not connected or filled is connected to the start point using the shortest path. After a branch is extracted the surrounding area is filled using the dilated radius estimate along the path. All quench points in the filled area are suppressed. The resulting per voxel graph is interpolated using the Douglas-Peucker method (Douglas and Peucker, 1973).

BRANCH EXTRACTION

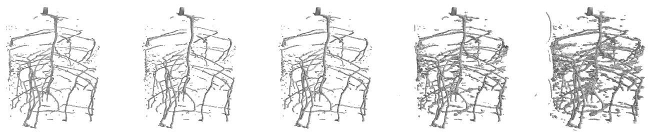


F1 SCORE FOR GRAPHS

- Generate dense point representation for manual and algorithmic extraction
- If points are close enough spatially and branch orientation matches, they correlate
- Using correlating points Precision and Recall are computed

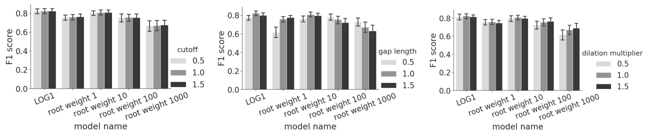
DATASET

- 22 Plant root MRI scans with human expert extraction
- Segmented by 5 different 3D UNet models
- LOG1 loss and root weighting 1, 10, 100, 1000 were employed



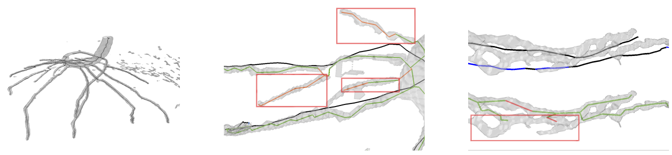
RESULTS DEPENDING ON INPUT AND PARAMETERS

- Performace was tested with respect to three algorithm parameters
- Models retaining correct surface perform best
- Models with low root weight loss to much structure
- Models with high root weight retain more noise and create merging structures



QUALITATIVE ASSESEMENT

- Branches get extracted by unique connections
- Root like structures not found in manual extraction were extracted
- Merging volumes lead to merged extraction



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

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