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Individual tree segmentation

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Introduction

For extracting tree attributes at a single tree scale, a segmentation of tree crowns is required. The Individual Tree Segmentation (ITS) classifies LiDAR point clouds into single trees with corresponding IDs. After segmentation, each point has an ID corresponding to the tree it belongs to. ITS methods can be generally grouped into two types, raster-based method and point cloud-based method.

Introduction

Raster-based algorithms detect trees (e.g., local maximum, image binarization, or template matching) and delineate crowns from the CHMs (e.g., valley-following, region-growing, or watershed segmentation) (Dalponte et al., 2018; Dalponte & Coomes, 2016; Pirotti et al., 2017; Puliti et al., 2020; Vandendaele et al., 2021).

To directly detect individual trees from the point cloud, a **point cloud-based algorithm** often requires Kmeans clustering, graph-based (Strîmbu & Strîmbu, 2015), kernel-based (Ferraz et al., 2012, 2016), or voxel-based tree segmentation techniques.

Introduction

For the purpose of individual tree crown detection and delineation (ITCD), numerous semi- and fully-automatic algorithms have been developed (Zhen et al., 2016). While one algorithm works well for a certain application, it might not be optimal for others. Some methods that performed well in softwood stands have shown to be less accurate in hardwood or mixed forests, especially in environments with significant variation in tree spacing, age, or size, or when the crowns overlap (Zhen et al., 2015). Although previous studies have made tremendous progress, ITCD research is still developing.

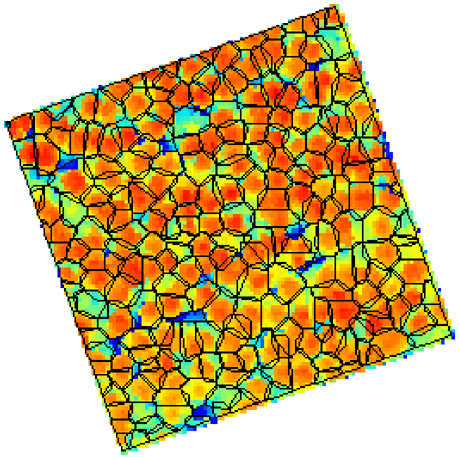
Content

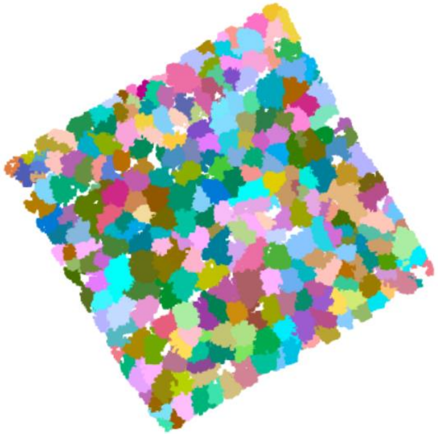
1. Raster-based approach

- Watershed
- Silva2016 (see Silva et al., 2016)
- Dalponte2016

2. Point cloud-based approach

- Li2012 (see Li et al., 2012)
- AMS3D

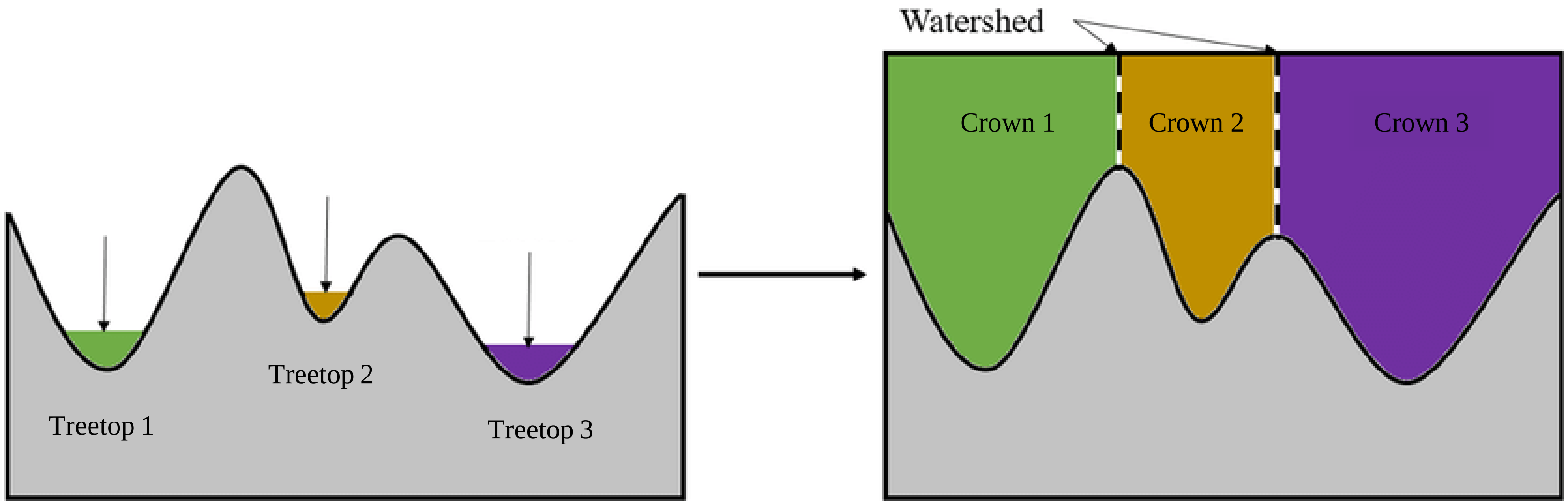




Watershed algorithm

- The watershed algorithm has been used in image processing primarily for object segmentation purposes
- The basic idea here is inverting the canopy height model (CHM), the treetops now become basins, and then starting to pour water into each basin. The water level then keeps rising, and at some point, they will touch each other, we can draw a separating line where water from bains touching, it becomes the border between tree crowns.

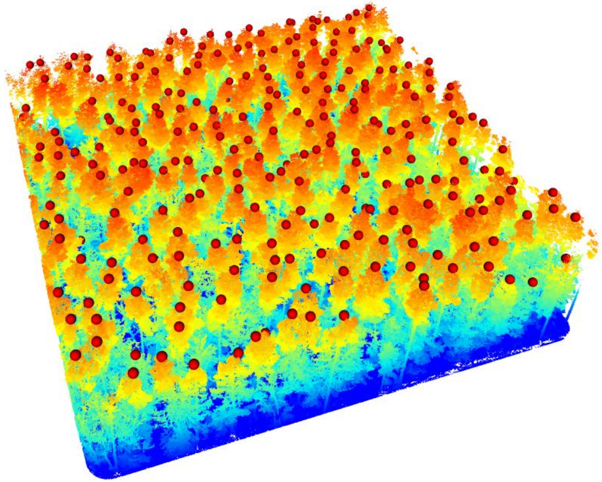
Watershed algorithm



Source: Duan et al., 2021 https://doi.org/10.3390/s21041365

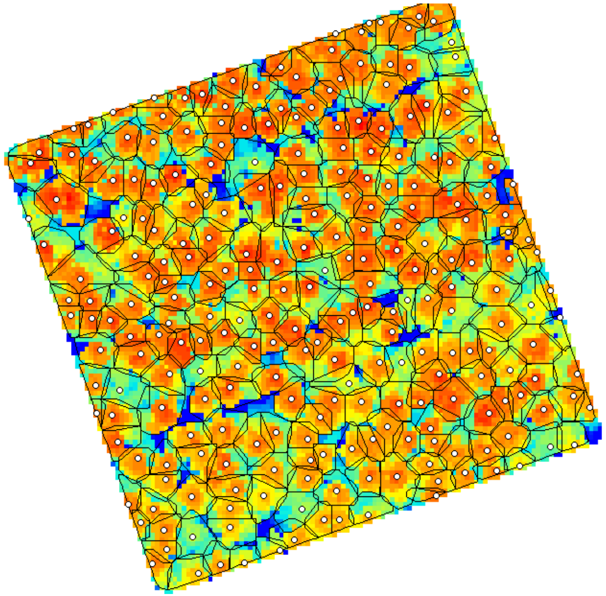
Dalponte2016 algorithm (seeded region growing)

1. Local Maximum Filter (LMF) algorithm finds treetops (red dots in the figure). A point is considered as a treetop if it is the highest point inside the predefined search window. The search window is an area where the LMF algorithm analyzes the neighborhood points. For example, if the window size is set to 5 m, the algorithm checks the neighboring points within a 2.5 m radius around the given point to see if the point is the highest in the local window.



Dalponte2016 algorithm (seeded region growing)

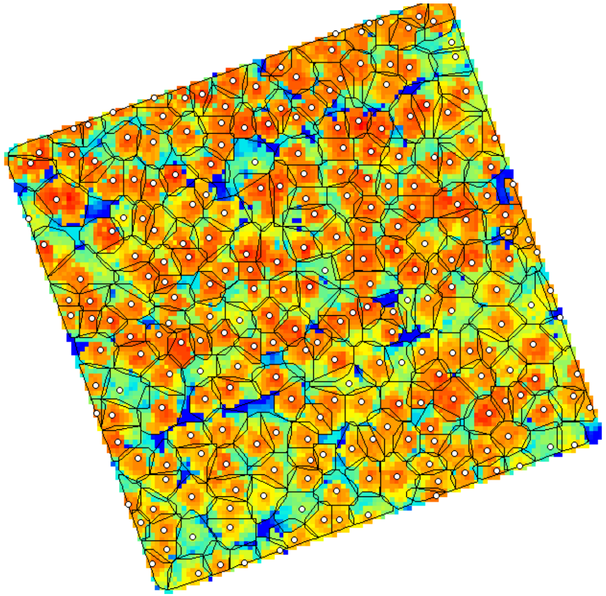
2. Then the treetops were overlaid with CHM, and the crown will then grow around the treetops. The algorithm checks the (height) value of neighboring pixels around the treetops.
3. If the height values of neighboring pixels fulfill certain criteria, these pixels get included in the crown. If not, exclude the pixel



Dalponte2016 algorithm (seeded region growing)

NOTE!

the raster-based approach relies on 2D CHM which only presents the top trees that are visible from above. Therefore, the subcanopy trees may not be detected.



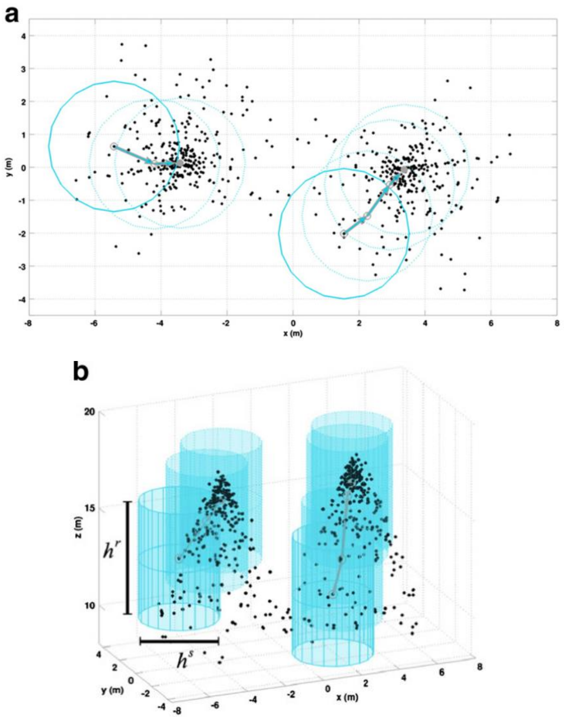
Recommended materials:

[Tree-centric mapping of forest carbon density from airborne laser scanning and hyperspectral data]

(Dalponte & Coomes, 2016)

Mean shift algorithm

The point cloud-based algorithm is expected to detect trees in all canopy layers. For every point in the point cloud, the algorithm builds a search window in cylinder kernel around them as in figure a and b. Then it finds all the points that fall inside the kernel and calculates the center of these points. The kernel is then shifted to the new center. From the new center, it again calculates a new center and keeps moving.



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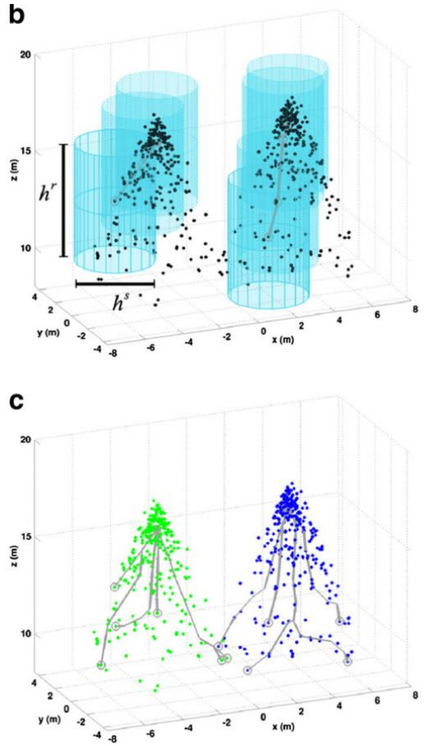
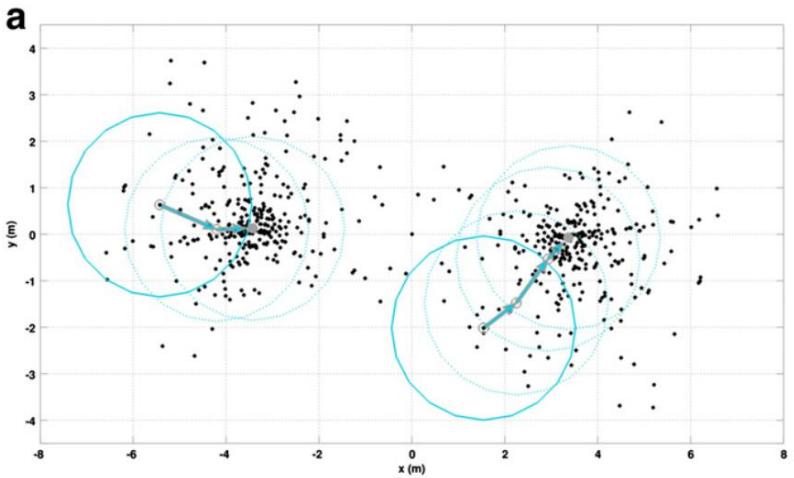
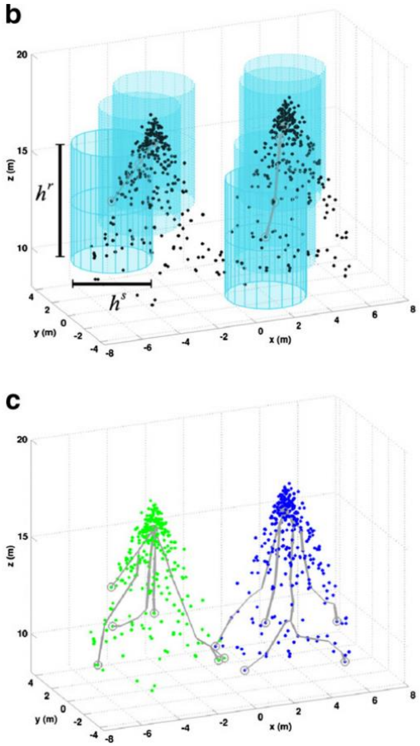
Mean shift algorithm

This procedure is repeated until the kernel’s center reaches a stable position which is a local maximum of point density and this position is assumed to be the center of a tree crown. In the end, as in figure c the lines represent the moving paths of the kernels. Many points will have kernels stop in the same location and these points are labeled as a tree.



Mean shift algorithm





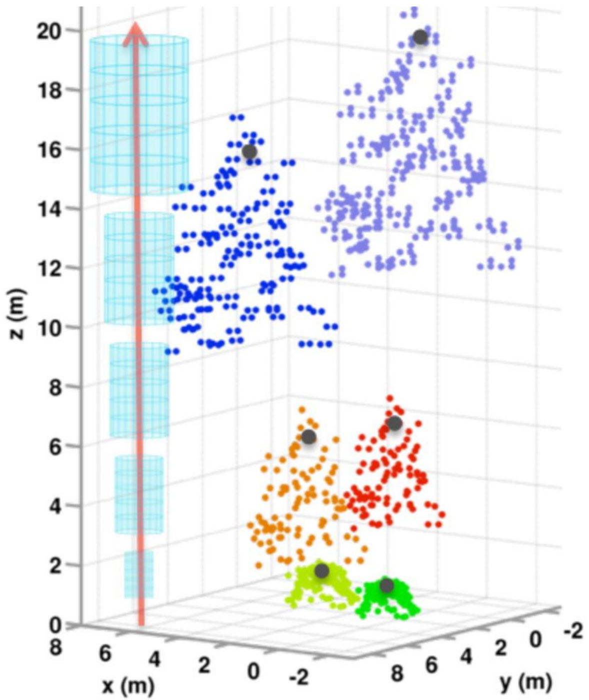
Source: Ferraz et al., 2012 https://doi.org/10.1016/j.rse.2012.01.020

a,b: Build kernels around points => calculate centers of points inside kernels => kernels move to new centers
c: Points have kernels stop at the same location form a tree

Mean shift algorithm

The size of kernel search windows (kernel length and diameter) is referred to as "kernel bandwidth", which is different for each point because it is dependent on the height of the point. The higher the point is, the larger kernel is created.

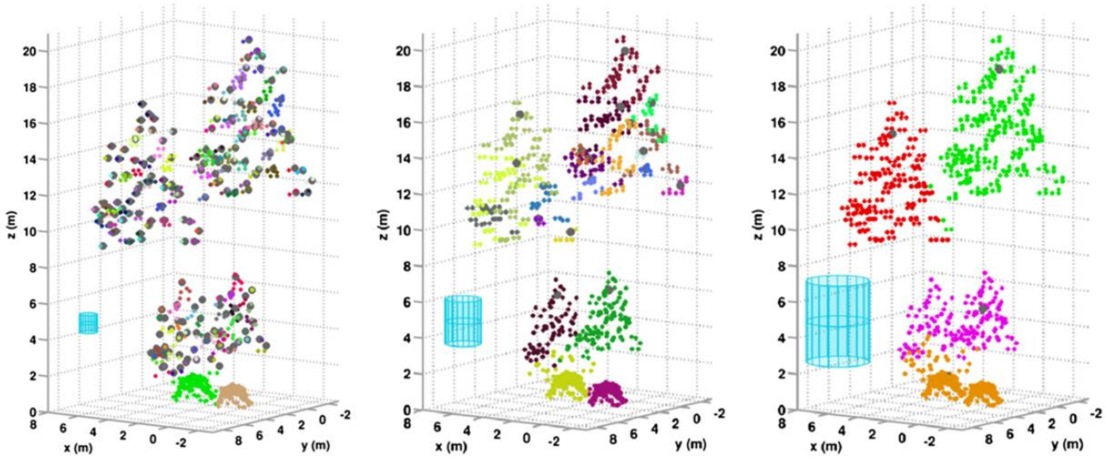
This height dependence assures to detect large crown clusters in the upper canopy by bigger kernels and small crown clusters in the lower canopy by smaller kernels (Cao et al., 2022)



Source: Ferraz et al., 2016 https://doi.org/10.1016/j.rse.2016.05.028

Mean shift algorithm

Source: Ferraz et al., 2012 https://doi.org/10.1016/j.rse.2012.01.020



Recommended materials:

3-D mapping of a multi-layered Mediterranean forest using ALS data (Ferraz et al., 2012)

Lidar detection of individual tree size in tropical forests (Ferraz et al., 2016)

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¡Thank you for your reading!

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