LEAF-WOOD SEPARATION AND TREE SKELETONIZATION FROM LOW RESOLUTION AND NOISY 3-D POINT CLOUDS

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1. Introduction

Three-dimensional characterization of trees and their structure plays a pivotal role in forestry-related applications. It facilitates the estimation of biomass, monitoring of forest inventory, and helps to assess forest-fire risks (Vicari et al., 2019; Terryn et al., 2020). For tree-specific studies, e.g., phenotyping-related or orchard yield measurement, localized acquisition by terrestrial laser scans (TLS) is a common choice (Ferrara et al., 2018; Li and Liu, 2019). However, such data acquisition source is inefficient and related analyses are challenged by the volume of data as well as the non-uniform shape of trees.

It is customary to approach point-cloud based tree-modeling by reconstructing their shape and then applying geometric completion steps through predefined rules and heuristics (Livny et al., 2010). However, some have identified the separation of leaves from branches as the preparatory step that precedes such reconstruction (Danson et al., 2014; Chaudhury and Godin, 2020). Though the separation of that kind has been approached by classifying the intensity channel (Danson et al., 2014), it is common to use local geometric cues, such as normal similarity, point density, and arrangement to facilitate this task (Vicari et al., 2019; Krishna Moorthy et al., 2020; Wang, 2020). When considering reconstruction, the scanned trees would generally appear bare of leaves leaving the focus to its structure. Capitulating on its cylindrical form, local fitting has seen some popularity (e.g., Burt et al., 2019), while others have attempted to identify a skeletal form by using node connectivity approaches, with the aid of octree- or voxel-based structures (Bucksch and Lindenbergh, 2008; Zhao et al., 2015). As they encode sophisticated logic, they may exhibit sensitivity to varying point densities. Alternative approaches iteratively converge to the skeletal form, where a Laplacian-based contraction has been applied by Cao et al. (2010), and L1-median skeleton form by Wang et al. (2016); Mei et al. (2017).

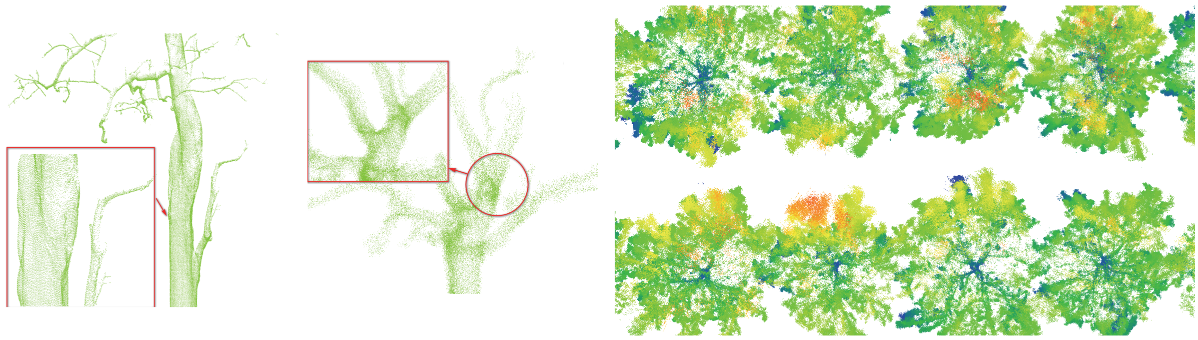

Figure 1: Tree related point-clouds, (left) TLS data acquired ∼50 m from object, (middle) handheld scanner (GEO-SLAM ZEB Revo RT), acquired 2 m from object; (right) bird view of the collected data, colored by elevation.

Most approaches utilize TLS data as their source, suggesting that the point clouds they process are dense and that the noise level is limited. When considering actual tree modeling on a larger scale, the use of stationary TLS is cumbersome and nonscalable. Instead, we consider in this paper a model that is driven by *handheld* scanning devices, which offer greater flexibility yet come at a cost of decreased resolution and accuracy (Figure. 1). Such characteristics limit the ability to perform leaf-wood separation in a simple manner and to identify the tree directly from the point cloud. They also require a greater focus on density-related effects and the impact of noise on the reconstruction.

2. Data and Methods

For our evaluation handheld scanning data of an almond orchard was collected (Figure 1). For the modelling, our proposed approach is structure-based where due to the noisy data, we consider the L1-median curve extraction (Equation 1) as our framework.

Given a pointset Q, our aim is to identify a set of characteristic skeleton points X subject to:

$$argmin \left|x_i - q_j\right| \theta\left(\left|x_i - q_j\right|\right) + R(X) \tag{1}$$

where $\theta(r) = \exp\left(-\frac{r^2}{h^2}\right)$ is a weight function and h is a density related term, $q_j \in Q$ is a point in the original set Q and $R(X)$ is regularization term (Huang et al., 2013). In evaluating affecting factors on the reconstruction, we demonstrate in Figure (2) how a direct application of a size-adaptive version of this form, where the value of h is increased between cycles, exhibits sensitivity in the presence of clutter. To filter the foliage, we evaluate leaf-removal models, particularly the recent one by Wang (2020), where local normal and proximity are considered as differentiating attributes. Figure (3) shows that because of the high-level of noise, results are partial, even when the normal similarity criterion is relaxed. Realizing these limiting factors when considering sparser and noisy data than that provided by TLS, our proposed approach places greater focus on robust measures and functions when quantifying features, while limiting the effect of derivatives in our evaluation. For that, we derive a shape-preserving model to attenuate the noise. Then, we show have a focus on neighborhood definition allows to robustify the feature computation for the presence of noise, clutter, and shape variation. In addition, and under the realization that the wood-leaf separation is a binary clustering form, we cast this problem as a graph-cuts formulation, demonstrating how it allows us to yield an optimal form. Using content aware modeling of both the overall tree point-cloud and then of its geometry, we provide a computationally efficient and reliable characterization of the sought form.

3. Results and Discussion

The application of our model is demonstrated in Figure (4) where we show how the trunk and branches are separated from the rest of the data and eliminate the clutter from the pointset. Additionally, in adapting the L1-median form, we demonstrate the application of a regularization form that encourages compliance with the overall trend of the surrounding neighborhood points. This facilitates convergence to the skeletal form within a small number of iterations.

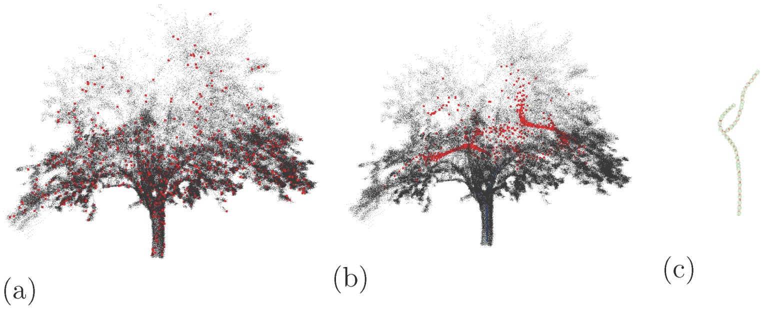

Figure 2: Skeleton extraction from the raw data using L1-median approach, a) seed points, b) intermediate results showing lack of convergence, c) extracted skeleton.

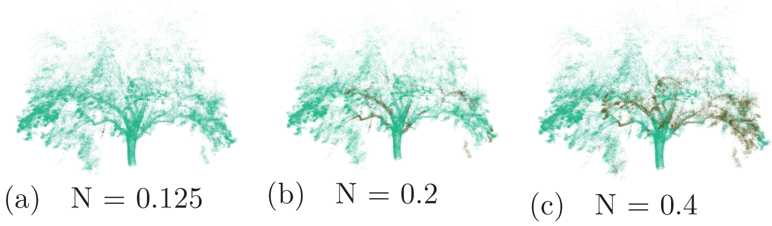

Figure 3. Wood-Leaf separation using Wang (2020). Thresholds are given according to the optimized configuration (0.1-0.2). Leaves and wood points are colored green and brown, respectively.

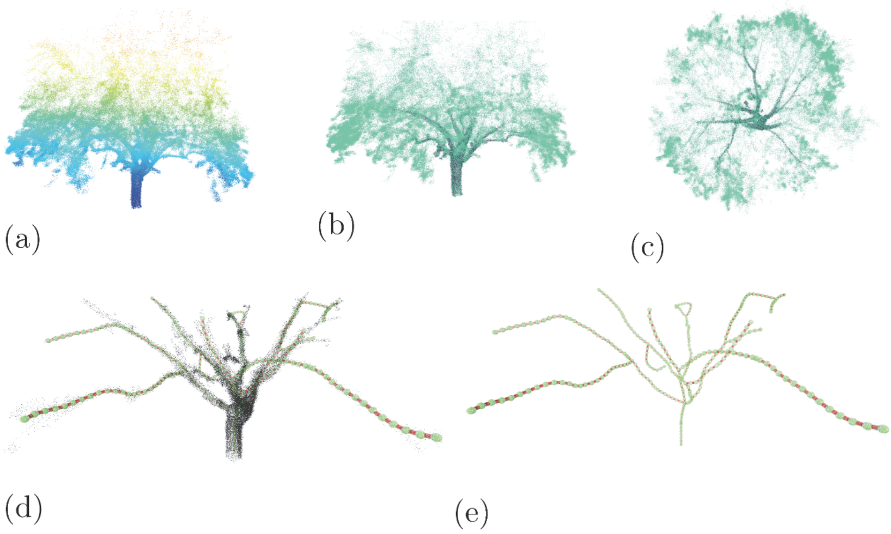

Figure 4. Our approach – (a-c) Wood-Leaf separation (leaves – green, trunk – black), (d-e) skeletonization results.

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