Accurate Plant Modeling based on the Real Light Incidence

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Abstract: In this paper, we propose a framework for accurate plant modeling constrained to actual plant-light interaction along a time-interval. To this end, several plant models have been generated by using data from different sources such as LiDAR scanning, optical cameras and multispectral sensors. In contrast to previous approaches that mostly focus on realistic rendering purposes, the main objective of our method is to improve the multi-view stereo reconstruction of plant structures and the prediction of the growth of existing plants according to the influence of real light incidence. Our experimental results are oriented to olive trees, which are formed by many thin branches and dense foliage. Plant reconstruction is a challenging task due to self-occlusion. Our approach is based on inverse modeling to generate a parametric model which describes how plants evolve in a time interval by considering the surrounding environment. A multispectral sensor has been used to characterize input plant models from reflectance values for each narrow-band. We propose the fusion of heterogeneous data to achieve a more accurate modeling of plant structure and the prediction of the branching fate.

1 INTRODUCTION

Realistic plant modeling is a well known topic of research in Computer Graphics. Its applications are mainly visualization and virtual reality. Other disciplines have also included plant reconstruction as a research objective, such as remote sensing (Prusinkiewicz, 2004) and biology (Omasa et al., 2006). Many plant modeling approaches have been developed over the last years. However, the dynamic plant behaviour, by considering the surrounding environment, remains a non-trivial and challenging task.

Procedural modeling approaches can efficiently synthesize the branching structure of existing real-world plant from a set of rule-based system (Beneš et al., 2011) and (Guo et al., 2018). In general, these methods are aimed to obtain visually acceptable results for rendering and simulation purposes, and therefore they are not directly oriented for 3D modeling real-world vegetation.

Geometry-based methods may also accurately reconstruct the skeletal structure of a tree, but the foliage is difficult to recreate (Xu et al., 2007; Livny et al., 2010). One of the most promising image-based methods is Structure-from-Motion (SfM), which is widely used to generate 3D point clouds from multiple overlapping images (Lou et al., 2014). However, this method arises some limitations, and the reconstruction of complex plant structures is prone to errors. On the other hand, other approaches may effectively reconstruct real plants using an inverse procedural method (Stava et al., 2010). In addition to geometrical data, some methods also regard additional environmental factors, such as light incidence (Stava et al., 2014), which influences the growth of the plant. However, these estimations are based on a probabilistic model, and not measured from the actual plant.

In this paper, we propose a several improvements for plant modeling constrained by the real plant-light interaction along a time interval. We aim to fuse the plant static reconstruction and inverse procedural modeling for plant growth prediction. In contrast to previous approaches that mostly focus on realistic rendering purposes, the main objective of our method is to monitor and predict the growth of real plants. We have tested our approach with olive trees, which are formed by a complex crown structure with many self-hidden branches and leaves. An inverse modeling process is applied for generating the parametric model to describe several botanic features. To this end, multispectral images are used to extract reflectance indices for each narrow-band to estimate the plant vigor and predict its next growth. A semantic classification of the plant shape is carried out by considering how plants reflect the light energy.

The paper is organized as follows. Firstly, a review of previous work on plant modeling is presented (Section 2) and we provide the general overview of

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our method (Section 3). In the following, experimental results are shown which are obtained from LiDAR and multiple images (Section 4) and the fusion of multispectral data to estimate the real light incidence to the plant model (Section 5). Finally, we discuss the contributions of the paper and the main topics for further research (Section 6).

2 RELATED WORK

Plant modeling is a classic topic of research in Computer Graphics. However, the main efforts have been made for visualization and virtual reality purposes. In this work, we apply plant modeling for the monitoring and prediction of the evolution of actual plants and bushes from extensive plantations. According to the literature, plant modeling approaches may be mainly classified into three categories: reconstruction from existing real-world plants, interactive modeling and procedural or rule-based systems, such as fractals (Oppenheimer, 1986) and L-Systems (Prusinkiewicz, 1986). Neither geometry-based nor interactive methods for tree shape reconstruction takes into account any environmental effects. On the other hand, procedural methods are capable to generate dynamic plant models whose evolution can be affected by changing conditions of the environment (Guo et al., 2018). There are two main methods which may be used for modeling existing real-world plants: plant static reconstruction and procedural modeling.

Plant Static Reconstruction. Geometry-based methods mainly depend on the input data, e.g., the image quality, environmental light during the capture process, the shape and texture of the target plant. In this way, 3D laser scanning can precisely reconstruct branching plants (Omasa et al., 2006) and can be used for the automatic reconstruction of the plant skeleton without overlapped trees segmentation (Livny et al., 2010). However, this technique implies some drawbacks as the sensitivity to occlusion, high device cost, and tedious application in many complex scenes, especially terrestrial laser scanning (TLS). As a solution of this problem the airborne LiDAR means a more efficient solution for scanning extensive plantations with an ever increasing precision.

On the other hand, multi-view stereo reconstruction is another category of methods which can be successfully used for tree reconstruction. It is based on a feature-matching process between multitude overlapping images. In this scope, the SfM method is commonly applied to generate a 3D point cloud of a plant by using several images (Quan et al., 2006). This technique overcomes some problems mentioned before, although it may not perform efficiently on complex and heterogeneous surfaces where the detection of key features is more complex. Moreover, this algorithm is based on the scale-invariant feature transform (SIFT) which may cause errors for the reconstruction of complex plant models (Lowe, 2004). Consequently, multi-view based realistic tree modeling with botanical features still pose several limitations. However, these problems might be partially solved by generating depth maps for each view, and fusing them into a dense point cloud reconstruction (Guo et al., 2018).

Procedural Modeling. Early approaches of plant modeling focus on the generation of repetitive patterns as fractals or L-Systems (Deussen et al., 1998). Instead of modeling directly from generative rules, guided procedural methods have been proposed to simulate the plant structure from an accurate point cloud based representation of its branching structure. Bennes et al. (Beneš et al., 2011) introduce guided procedural modeling with several geometric constraints. Nowadays, the reconstruction from point clouds has received considerable attention (Berger et al., 2017). In this way, procedural models can be transformed into certain shapes depending on the point cloud input that are acquired with static plant modeling. Modeling trees according to desired shapes is important for many applications. However, procedural methods have some drawbacks due to the complexity to determine a valid set of input parameters, such as branching angle, apical and lateral light effects, pruning factors, growth rate, etc. These features are very important for the structure of young trees but they become less relevant for mature plants. Stava et al. (Stava et al., 2014) proposed an inverse procedural modeling method for trees, based on a novel parametric model that uses Monte Carlo Markov Chains (MCMC) for calculating the optimal set of procedural parameters. However, all these approaches generate static branching structures rather than modeling dynamic plant behavior.

Procedural methods are capable of generating tree models by explicitly considering the environment. Recent approaches are focused on providing more efficient ways for plant-environment interaction modeling. Palubicki et al. (Palubicki et al., 2009) optimize branch distribution with space colonization method (Runions et al., 2007) and local competition for light resources. In each iteration, the space surrounding of each bud and the optimal direction of shoot growth are calculated. Both values are needed to create a tree structure by simulating real environmental properties. Later, Lei Yi et al. (Yi et al., 2015) demonstrates the sensitivity of branching distribution to ambient light

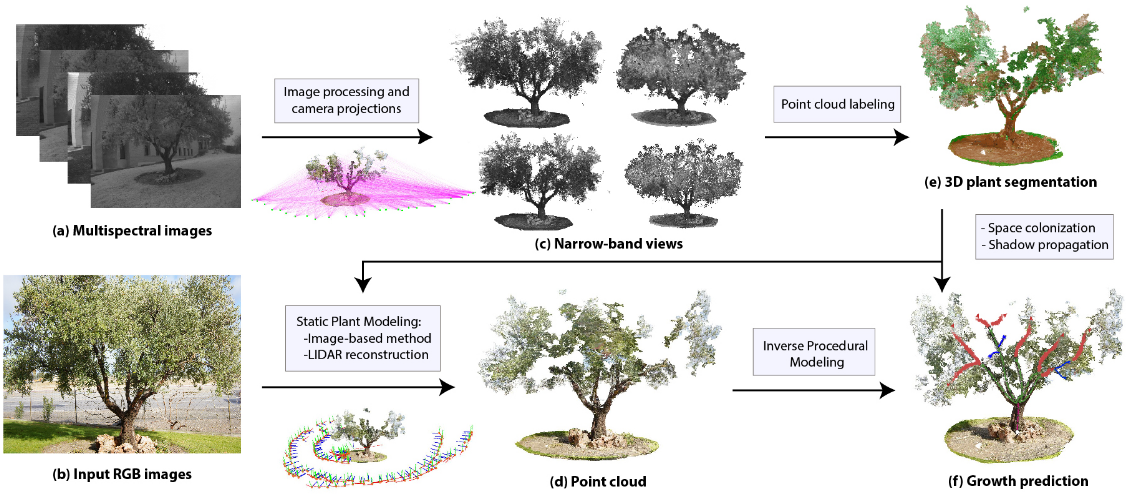

Figure 1: Overview of the method for olive tree reconstruction from the fusion of multispectral data.

and how each branch influences to others.

In addition, an important research topic in Ecology and Biology focuses on plant phenotyping and measuring leaf chlorophyll concentration, in order to study each growing stage of plants from image-based remote sensing (Moran et al., 1997). In contrast to the simply visual detection of diseases, narrow-band sensors are commonly used to measure plant changes considering how the vegetation interacts with the ambient light of the surrounding environment (Candiago et al., 2015). Unfavorable plant growing results in morphological, physiological and biochemical changes that are determined by the quantity of absorbed or reflected light. Leaf spectral reflectance provides multiple key features for assessing plant health; however, leaves typically have a low reflectance in the visible spectral due to the high chlorophyll absorption (Peñuelas and Filella, 1998). Multispectral sensors capture several spectral bands to detect many properties, such as drought stress, heat stress, nutrient content and plant biomass. Current approaches mostly provide a 2D-based analysis for plant diseases detection (Thomas et al., 2018), image-based vegetation segmentation (Suh et al., 2018), plant phenotyping through ground-based sensors (Sankaran et al., 2010) and LiDAR and hyperspectral remotely sensed data (Hakkenberg et al., 2018). Although many of these methods have certain capabilities to describe growth behaviour, it is quite difficult to acquire several plant traits which are not directly visible from remote sensing imagery. This issue might be overcome through a faithful 3D modeling of the real plant for a readily comprehensive assessment of complex plant features (Klodt and Cremers, 2014).

3 OVERVIEW

In this paper, we propose a method for dynamic plant modeling constrained to actual plant-light interaction along a time-interval. The incident light is obtained from several spectral bands and used to improve the plant static modeling. The main goal is to generate accurate plant models for monitoring extensive plantations using several 3D capture techniques, working at different levels of detail. In this work, we focus on the reconstruction and characterization of a single tree model. An inverse modeling process generates the parametric model from multispectral data which provide several features to describe the plant vigor such as the reflectance index, chlorophyll fluorescence or leaves temperature. The generation of the tree structure by procedural methods is constrained by several constraints related to the plant status. We also consider time-lapse data for analyzing the evolution of the plant along a period. In addition, multispectral data may be the support for performing reasonably realistic predictions.

The flow diagram of our framework illustrates the overall process (Figure 1). The first step of our method is the accurate point cloud reconstruction of each plant at a detailed level. The first step of our method is the plant static modeling of the olive tree from multi-view stereo reconstruction method and terrestrial LiDAR scanning. Both geometry models may be the input for our framework which is based on multispectral image projection from multiple views. Data from narrow-band views are used to carry out an early segmentation of the point cloud, in order to simplify the number of features used in the reconstruction. In the following, an inverse procedural modeling is performed on the point cloud to overcome reconstructing issues as self-hidden branches and leaves of the plant. To this end, for each view a reflectance map is computed for the automatic model segmentation. This technique is useful to determine several constraints for the guided structure generation. We integrate this into a rule-based growing system, that also uses a variation of space colonization (Runions et al., 2007) and shadow-propagation (Palubicki, 2012). As our method is based on the change in light distribution from several spectral bands, the illumination of different part of the tree is calculated and used to improve the data-driven reconstruction. In addition, the spatio-temporal analysis of the plant behavior provides us real historic data for the growth prediction.

4 POINT CLOUD RECONSTRUCTION

One of the main steps of our solution consists of obtaining three-dimensional information from real plants to complete it with data obtained from multispectral sensors. For this purpose, several known techniques might be applied to generate 3D models of existing real-world plants. This process can be carried out for each plant or using batches, depending on the technology used for capturing the data. We mainly used two methods: Light Detection and Ranging (LiDAR), and the image-based reconstruction. These methods produce distinct results, that is, point clouds with different attributes and spatial distribution. However, both of them offer spatial data with enough precision to be used in the following steps of the modeling.

LiDAR. This 3D scanning technique determines the distance to a point in space by timing the round trip time of a light pulse typically fired by a laser diode. The time that passes until the reflected light is captured by a detector is timed. Visible (green) or invisible (near infrared or NIR) lasers are usually used. Typical time-of-flight laser scanners can measure the distance of several hundred points per second (high-density clouds). Airborne LiDAR can scan a wide area of terrain in a short period of time, and this is the main reason for using it with the aim of monitoring the temporal evolution of entire plantations. The main drawback is that 3D scanning is a process prone to occlusion, especially when capturing plants (Figure 2). However, scanned plants have a higher resolution than image-based models, hence, more accurate guide is generated for the inverse modeling.

In order to obtain the skeleton of a tree from the scanned point cloud, we follow a similar approach as the first step of the algorithm presented in (Xu et al., 2007). Due to the typical incompleteness of the point clouds produced by LiDAR, additional branches have to be synthesized to complete the tree topology, especially the crown. We use cluster edges in a spanning graph to reconstruct the tree skeleton. However, leaves are not randomly added to the fine branches as presented in (Xu et al., 2007). Instead, we rely only on the scanned data, because our method is targeted to the monitoring of actual leaves. Our experiments were mainly targeted to olive trees. This type of plant is formed by many branches and a very dense crown with multitude of leaves of different sizes. This aggravates the occlusion of the inner part of the tree.

Figure 2: Point cloud from terrestrial LiDAR scanner.

Multi-view Stereo Reconstruction. This method supposes a simplification of the technique of stereo vision for the case of a single camera that takes images from different positions. Computer vision techniques are used to calculate matching points, since the positions of the camera do not have scale and orientation information in relation to the object to be scanned. This low cost technique is based on an adjustment procedure that uses a database of features. Those features are automatically extracted from a set of multiple overlapping images. We have used a combination of SfM and Patch-based MultiView Stereo (PMVS) to obtain dense point clouds from trees. The data obtained with this method can complete the data obtained with LiDAR when necessary, especially with occluded zones at low heights. SfM is a technique for producing dense point clouds based on a feature matching process. However, it does not produce accurate results on plant images with repetitive or similar feature properties (Guo et al., 2018). For this reason, we only use the part of SfM that estimates the stereo camera position for each of the shots. Then, PMVS produces a point cloud based on the features found, taking into account the visibility constraints. This combination of SfM and PMVS produces better results, but it still has problems with occlusions and the performance does not scale well. In order to improve the process, a novelty of our method consists of using images from the multispectral camera for an early segmentation of points, based on multispectral analysis. This step allows us to extract only the points corresponding to trunks and branches, omitting all the leaves, which are precisely the part of the plant that causes all the feature matching issues. After the views matching, all points are used for the resulting dense point cloud (Figure 3). This process greatly increases the precision of the multi-view reconstruction, especially with overlapped trees. Later, we use a point clustering process for the inverted modeling of the tree skeleton. We also plan to incorporate the method presented in (Guo et al., 2018). It uses a depth map based reconstruction algorithm. For each view, a dense depth map is computed. Then, all maps are projected into a single point cloud model by considering visibility. Our contribution at this point involves the addition of multispectral information to the depth maps. It provides the removal of all superfluous information from each map, increasing the performance of the process.

Figure 3: Point cloud from Structure-from-Motion.

5 PLANT-LIGHT INTERACTION

The surrounding environment plays a key role for the growing process of trees. The crown shape and branching structure are directly determined by several environmental effects. The light energy is considered as the main factor for branch shooting and it is calculated by sampling the environmental space. For this purpose, plant models are decomposed into a grid of voxels. In this way, a coarse estimation of the interaction of light with each bud is computed (Palubicki et al., 2009). In general, the exposure of each bud to light is an estimation based on the plant space classification into a grid of voxels. In this way, the shadow propagation method is applied to calculate the bud fate by selecting the adjacent voxel with the lowest shadow value. In terms of realistic plant behaviour according to the light sensitivity, multispectral sensors may be used to capture the reflected energy in various spectral bands.

In this work we have targeted the olive tree as the main objective. It has been observed by four spectral bands: Green (530nm-570nm), NIR (770nm-810nm),

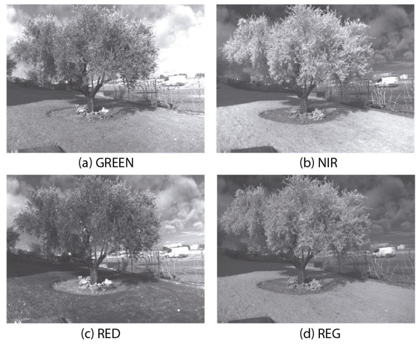

Figure 4: Narrow-band channels for each capture.

Red (640nm-680nm) and REG (730nm-840nm) (Figure 4). For each one, the influence of the sunlight is studied for multiple purposes: (1) the 3D reconstruction of the tree structure from multi-views, (2) the plant space decomposition and (3) the prediction of natural growth process. To this end, our method uses as input either some geometric tree models by LiDAR scans or multiple overlapping images. Once the 3D point cloud has been extracted, reflectance maps are computed for each band. Unlike previous works, which are based on a coarse light propagation, we calculate the actual light reflectance value (LRV) for each plant from multispectral image processing. Following, a backward projection is carried out for point cloud labeling (Figure 5). For this purpose, the fisheye distortion model of narrow-band images is applied for mapping the distorted pixel coordinates to the 3D points.

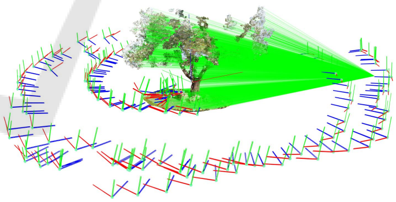

Figure 5: The multispectral images are back-projected to the input point-cloud.

Plant Segmentation. Since the input point cloud may not be completed and many branches have not been reconstructed due to the occlusion with each others, a novel 3D classification method is proposed. It is based on the inclusion of reflectance values to complete the branching structure and the foliage. As plants become healthier, the intensity of reflectance increases in the NIR band and decreases in the Red band, which is the physical basis for most vegetation indices. NDVI (Normalized Difference Vegetation Index) value arguably indicates the plant vigor and is also effective for distinguishing vegetation from branches, trunk and soil. As Figure 6 shows, the olive tree is subdivided in two classes which correspond to the foliage and the ramification of branches. This method provides the capability to reduce the noise of the 3D model which is produced by the reconstruction of leaves and narrow branches. Therefore, several improvements are in progress aimed for plant modeling from multi-view images by considering the search of key points specifically in branches and trunk.

Figure 6: Plant model segmentation.

Plant Space Decomposition. In addition, instead of performing a voxelization of the plant space, we carry out a semantic subdivision of the model for studying shadow propagation. According to previous plant dissemination, a 3D clustering method is proposed for the inverse modeling of the tree structure (Figure 7). We focus on the classification of several point groups to identify the plant skeleton and improve the guided modeling of the real tree shape. In the image below, the soil, trunk and main branches are joined to the same cluster. This group shares similar reflectance values, ranging from 0 to 0.4 and several soft geometric constraints such as distance, normal direction, cluster volume, etc. Moreover, the plant crown is subdivided into six clusters to estimate the canopy density and the spanning for each branch.

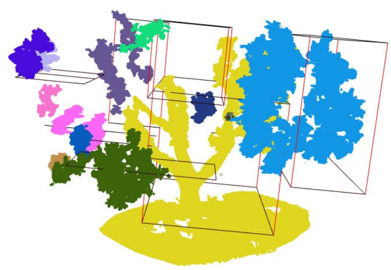

Figure 7: Semantic classification of the plant shape.

Procedural Modeling. The influence of the surrounding environment should be considered for the prediction of the plant growth. In this context, the procedural modeling is capable to simulate the adaptivity of trees by considering several environmental effects. In general, the space colonization and the shadow propagation are the most used methods. However, unlike previous works, which are based on a coarse estimate of bud exposure to calculate the optimal growing direction, our method takes the real light incidence and the photosynthetic activity of plants from multispectral imagery. Consequently, it provides several parameters to predict the next growth stage according to the reflectance index which may determine the pruning factor, phototropism and gravitropism, branching angle, etc. Our hypothesis is based on estimating the growth rate for each region of the plant due to some parts grow faster than others.

6 CONCLUSIONS AND FUTURE WORK

We have introduced main contributions of our research in progress. A novel framework is provided for plant modeling according to the plant-light interaction. The key feature of our method is the combination of geometry plant models to semantic data from multispectral imagery. In summary, plant modeling without the influence of the surrounding environment results to static and unrealistic tree representations. This work is focused on the olive tree structure and their interactions with the environmental light. In this paper, several techniques for plant modeling and novel methods based on spatial classification have been applied to estimate the growing shoot from the light-based plant behaviour. To this end, a plant segmentation is carried out to disseminate the branching structure to the foliage. Then, a semantic and volumetric plant space decomposition is proposed for spatial pooling by several features in common. Moreover, a historic set of spectral images have been acquired to predict next growing stages of target trees from the reflectance absorption.

Several open problems may be approached for future work. For the monitoring of extensive plantations, it is not feasible to store a dense point cloud for every plant or bush. First, we would generalize our method to model larger scale scenes, such as real ecosystem of even a forest. Second, since the plant space decomposition, we focus on generating a rule-based system to reconstruct self-hidden geometry from previous knowledge of how each plant regions interact with the environment. Finally, the development of a robust predictive model based on multispectral or hiperspectral data to simulate the growing process under different environmental effects.

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