Synthesizing trees from samples

Rui Wang Wei Hua Zilong Dong Hujun Bao Qunsheng Peng
State Key Lab of CAD&CG, Zhejiang University, China
E-mail: {rwang|huawei|zldong|bao|peng}@cad.zju.edu.cn

Abstract

In this paper, we propose a novel tree modeling approach, synthesizing new trees from samples. First, we capture real world trees as samples by image-based modeling or laser scanning techniques. Then, we present a two-level statistical tree model and design a maximum likelihood estimation algorithm to extract it from samples. At the low level in the tree model, groups of similar organs are clustered to depict tree organ details statistically. At the high level, a set of transitions between clusters is outlined to describe the stochastic distribution of organs. Experimental results show that our two-level model extracted from samples is capable of synthesizing new trees similar, yet visually different.

Keywords: Tree Representation and Modeling, Modeling from samples

1. Introduction

In computer graphics, modeling trees with high fidelity is an interesting but hard problem. In general, ordinary 3D modeling approaches [1][3][8][9][10] are capable of generating various kinds of trees; however, the results heavily rely on user's biological knowledge and modeling experience. Another modeling technique is based on an inverse-procedure, which recovers tree models from photographs [2][5]. Nevertheless, these solutions aimed at resembling the trees on photographs rather than retrieve the botanical principles that can be used to generate new trees.

In this paper, we propose a novel tree modeling approach, efficiently synthesizing trees from a set of tree samples captured from real world. A two-level statistical model is used to represent trees. At the low level in the model, repetitive organs, which are in similar shapes and branching structures, are clustered together. In each cluster, statistical distributions are used to describe organ details. At the high level, we assume the distribution of these clustered organs, or namely the transitions between clusters, follows the first-order Semi-Markov dynamics, which is represented by a transition matrix. To capture more faithful tree samples, we use the laser scanning and image-based modeling techniques. Then, a maximum likelihood estimation algorithm is designed to find the best classifications of organs and their transitions. Once these clusters and their transitions are learnt, they are used to synthesize new trees, which are statistically similar to, yet visually different.

1.1. Related work

Tree modeling. Ulam[10] employed the concept of cellular automata to propose a first tree model. Later, Fractals [8] and rewrite systems [9] use a set of rules and a rewriting mechanism to describe the structure plant. Recently, some pieces of interactive software to design the model or the rewriting rules have been developed [3] [1].

Capturing real-world tree. Shlyakhter [5] used the plant silhouettes on multi-view images to obtain a volume representation for a tree. Reche et al. [2] presented another image-based volumetric representation, in which a tree is composite of a set of grids with view-dependent textures.

Textons and Markov Model. Our tree synthesis algorithm is inspired by the texture synthesis algorithms. A texture can be regarded as a combination of textons[4] and the distribution of textons is regarded as a Markov random field. For tree modeling, some biological researches [11] have pointed out that the architecture of a plant relates to a Markov process.

1.2. Overview of our approach

Our approach takes three steps to model new trees: (1) Recovering tree samples from real world. (2) Analyzing the recovered tree samples to build the two-level statistical model. (3) Synthesizing new trees based on the learnt two-level model. (Figure1)

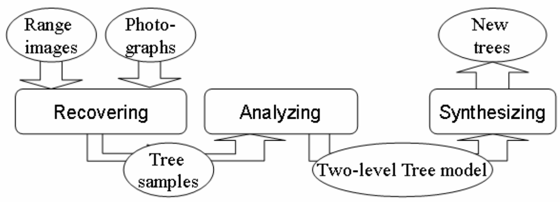


Figure 1. Algorithm Overview

2. Recovering

2.1 Sample Representation

A tree sample is represented by a pair, organ set $\boldsymbol{O}$ and organ connectivity $\boldsymbol{B}$. $\boldsymbol{O}$ is a partially ordered set of organs and $\boldsymbol{B}$ enumerates existed directed connections between two organs in $\boldsymbol{O}$. In the tree sample, we assume there are $\boldsymbol{M}$ organs, namely $\boldsymbol{O}=\{o_1,o_2,\ldots,o_M\}$. Organ connectivity is defined by $\boldsymbol{B}=\{\mathrm{b}(o, o')|o \in \boldsymbol{O}, o' \in \boldsymbol{O}$, and o' grows from $o\}$.

2.2 Recovering from range images

The range camera is used to recover non-foliage trees in winter. Accounting for the accuracy, for each tree multiple views are shot. On each view, points with depths on 2D skeletons of stems are automatically extracted and then registered in a global coordinate (Figure 2).

(a) (b) (c) (d)

Figure 2. *Recovered Stems from range points. (a) points clouds. (b) linked points (c) points are fitted by Bezier splines and (d) final extracted stems*

2.3 Recovering from photographs

For foliage trees, due to self-occlusion, it is hard to recover trees automatically. We induct user's interactions to recover samples. For each type of organs, different interactive tools are developed to help user to do recovering from calibrated photographs. Under the statistical assumption, in our model only a portion of a real world tree is needed to recover, which greatly reduces the cost for the acquisition.

3. Analyzing

3.1 A two-level statistical Model

We propose a two-level statistical model to characterize the stochastic nature of the same kind of trees. At the low level, organs are classified into different clusters, each of which is used to depict similar features of organs statistically. At the high level, the transitions of these clusters are used to describe the stochastic distribution of tree organs. Thus, a kind of trees can be represented by a set of clusters X={x1,x2,…,xN} together with the transitions of the clusters A (a transition matrix).

The above model is equivalent to a directed graph, in which each node is a cluster and the weight on each directed arc is the transition. Such kind of model has been widely applied in texture synthesis, video texture and motion textures. However, unlike conventional Markov Models[6], we use hybrid transitions, which is not only probabilities but also with more statistical features (location and direction distributions).

3.2. Learning Single Sample

Given a tree sample ($\boldsymbol{O}$, $\boldsymbol{B}$), our approach learns the tree model parameters ($\boldsymbol{X}$, $\boldsymbol{A}$) by finding a maximum likelihood solution.

$$(\hat{\boldsymbol{X}},\hat{\boldsymbol{A}}) = \arg\max_{(\boldsymbol{X},\boldsymbol{A})} P(\boldsymbol{O},\boldsymbol{B} \mid \boldsymbol{X},\boldsymbol{A}) \qquad (1)$$

Considering $\boldsymbol{X}$ and $\boldsymbol{A}$ as hidden variables, we adopt the EM algorithm [7] to solve the maximum likelihood problem. All organs in the tree sample are classified by a k-mean algorithm. In the first step (E-step), the distribution of features for each organ cluster and the transitions $\boldsymbol{A}$ among clusters are estimated respectively. In the second step (M-step), according to the estimated distribution and transitions, all organs are reclassified and the clusters are updated. The E- and M-steps are executed repeatedly until the clusters cannot be updated.

3.2. Learning Multi-Samples

Given K samples ($\boldsymbol{O}_1$, $\boldsymbol{B}_1$),…,($\boldsymbol{O}_K$,$\boldsymbol{B}_K$), Eq.(2) can be extended to

$$\begin{aligned}(\hat{\boldsymbol{X}},\hat{\boldsymbol{A}}) &= \arg\max_{(\boldsymbol{X},\boldsymbol{A})} P((\boldsymbol{O}_1,\boldsymbol{B}_1),\ldots,(\boldsymbol{O}_K,\boldsymbol{B}_K) \mid \boldsymbol{X},\boldsymbol{A}) \qquad (2)\\ &= \arg\max_{(\boldsymbol{X},\boldsymbol{A})} \sum_{i=1}^{K} P((\boldsymbol{O}_i,\boldsymbol{B}_i) \mid \boldsymbol{X},\boldsymbol{A})\end{aligned}$$

The solution for Eq.(2) is similar to Eq.(1) with minor modifications. At each E-step, $\boldsymbol{X}$ and $\boldsymbol{A}$ are estimated from all organs in $\bigcup_{i=1}^{K} \boldsymbol{O}_i$. At each M-step, the classification is derived by maximizing the likelihood in each sample ($\boldsymbol{O}_i$, $\boldsymbol{B}_i$).

4. Synthesizing

With learnt two-level model, it is efficient to synthesize many new statistically similar trees by randomly sampling from {X, A}. Since our tree model distinguishes the global organs distribution (transition matrix A) and the local shape distribution (clusters X), we develop a two-step approach to synthesize new trees. Firstly, the new tree's structure is synthesized by a recursive algorithm. It starts at the root cluster in the set X. For the current cluster $\boldsymbol{x}_i$, children cluster are randomly chosen from the transition matrix. Then, along the tree structure, organs are generated consequently.

5. Implementation and Results

5.1 Results of Recovering

We used DeltaSphere™-3000 3D Scene Digitizer to scan trees. For each tree, 2 to 4 views were shot. It took about 5 to 10 minutes automatically and extra 2-3 hours interactively to recovering stems of one sample on an Intel Pentium IV 2.4GHz computer with 1GB memory. In our interactive image-based plant modeling process, it usually took 4 or 5 hours to recover organs from photographs for one sample. Some recovered results are shown in Figure 7.

5.2 Results of Analyzing

Our learning algorithm, EM algorithm, iteratively clusters organs from given samples. Initially, the first classification is given by a k-mean clustering algorithm. Figure 4 illustrates a few steps of iterations in the stems classification procedural, in which stems clustered in the same planton are shown in the same color and the variation of colors between iterations indicates different classifications.

5.3 Results of Synthesis

Some synthesis results are shown in Figure 5. Synthesized organs are converted into meshes and exported to 3D studio Max for final rendering. For stems, a generalized mesh subdivision algorithm is used to achieve natural transitions at the branching locations. Stems' and leave's textures are recovered from captured images.

6. Conclusion and Discussion

In this paper, we propose an automatic analyzing and synthesizing approach for modeling realistic trees from samples. A two-level statistical model is addressed to represent trees. A maximum likelihood estimation is applied to learn the statistical properties of trees. Under our two-level model, the similar, but not recognizably the same trees can be synthesized efficiently.

References

[1] F. Boudon, P. Prusinkiewicz, P. Federl, C. Godin, R. Karwowski, "Interactive Design of Bonsai Tree Models". *Computer Graphics Forum* 22 (3), 2003, pp. 591-599,

[2] A. RECHE, I. MARTIN, and G. DRETTAKIS. "Volumetric Reconstruction and Interactive Rendering of Trees from Photographs". SIGGRAPH Conference Proceedings 2004

[3] B. Lintermann, and O. Deussen, "Interactive Modeling of Plants", *Computer Graphics and Applications*, 19(1):56–65, 1.

[4] B. Julesz, Textons, the elements of texture perception and their interactions. Nature, 290:91– 97, 1981.

[5] I. Shlyakhter, M. Rozenoer, J. Dorsey, and S. Teller, "Reconstructing 3D Tree Models from Instrumented Photographs", *Computer Graphics and Applications*, 19(1), 1999.

[6] L. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition". Proceedings of the IEEE, 77(2):257– 285, February 1989.

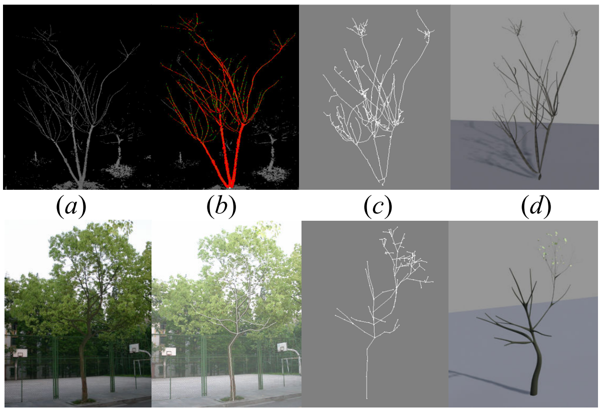
[7] N. M. Dempster, A. P. Laird, and B. Rubind, "Maximum likelihood from incomplete data via the EM algorithm". J. R. Statist. Soc. B, 39:185–197, 1977

[8] P. E. Oppenheimer: "Real-Time Design and Animation of Fractal Plants and Trees". In Computer Graphics (SIGGRAPH 86 Conference Proceedings) (1986), vol. 20, pp. 55–64.

[9] Prusinkiewicz P., and Lindenmayer A.: The Algorithmic Beauty of Plants. Springer-Verlag, New York, 1996.

[10] S. M. Ulam, "On Some Mathematical Problems Connected with Patterns of Growth of Figures", *Proceedings of the Symposia in Applied Mathematics*, Vol. 14, p215-224, 1962

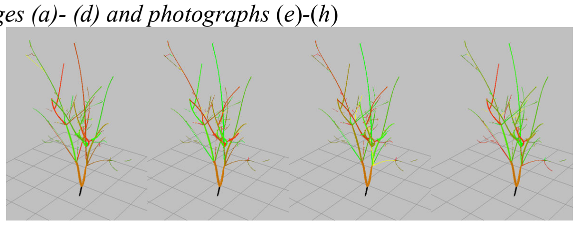
[11] Y. Guédon, D. Barthélémy, Y. Caraglio, and E. Costes, Pattern analysis in branching and axillary flowering sequences. Journal of Theoretical Biology 212, 481-520. 2001



(*a*) (*b*) (*c*) (*d*)

(*e*) (*f*) (*g*) (*h*)

Figure 3. *Procedure of recovering samples from range images (a)- (d) and photographs* (*e*)-(*h*)



(*a*) (*b*) (*c*) (*d*)

Figure 4. *Classifications of stems in the EM algorithm. Stems in the same color are classified into the same cluster.*

(*a*) (*b*) (*c*) (*d*)

Figure 5. *Synthesized Results.* (*a*), (*b*) *are synthesized from samples captured by range images and;* (*c*), (*d*) *are synthesized from samples captured by photographs.*