Shape from Silhouette Probability Maps:
reconstruction of thin objects in the presence of silhouette extraction and calibration error

Amy Tabb amy.tabb@ars.usda.gov Appalachian Fruit Research Station, Agricultural Research Service, US Department of Agriculture, in Kearneysville, West Virginia

1 Problem Description

The reconstruction of leafless fruit trees has the following applications:

- Automated measurements for physiological and genetic studies
- Needed for robotic pruning

Modern apple planting systems consist of trees that are roughly 3 feet (0.9 m) in diameter and 14 feet tall (4.27 m). The type of trees we are considering use a *central leader* architecture. The trees are planted in rows, as below:

Figure 1: Tall spindle apple trees with trellis. ©Jon Clements

There are various difficulties associated with reconstructing leafless trees:

- The outdoor environment introduces illumination variations
- Wind and machine vibrations can alter camera calibration
- Branches are thin as they emanate from the central leader
- There is great variation in shape among trees despite uniform application of a specific training system.

Figure 2: Secondary branches emanating from the central leader. ©Edwin Winzeler

2 Assumptions

We pursue a Shape from Silhouette approach for reconstruction, with the following assumptions:

- There are no leaves on the tree; the tree is in its dormant state
- Small camera calibration error exists in our datasets
- Silhouette extraction error exists in our datasets

3 Contributions

When binary-valued silhouettes are used, we call this the Shape from Inconsistent Silhouette problem (**SfIS**). When continuous-valued silhouettes are used, we call this the Shape from Silhouette Probability Maps problem (**SfSPM**).

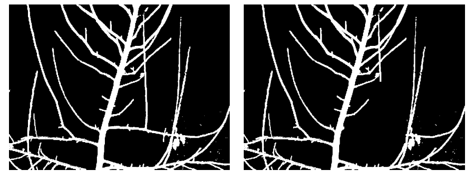
Our approach provides the following contributions:

- Does not depend on parameters set by users
- Penalizes false negative and false positive error equally
- SfIS and SfSPM problems are treated identically
- Reconstructs large, thin objects with silhouette and camera calibration error.

4 Formulation of a Silhouette Inconsistency Error function

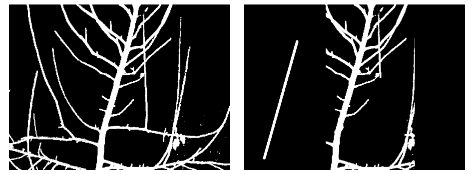
We cast the reconstruction problem as a minimization problem: labeling voxels $\mathbf{x}$ as occupied or empty such that a cost function, $SIE(\mathbb{I}, \mathbf{x})$, is minimized.

The SIE function represents the absolute difference between the input SPMs and reconstruction images.



(a) SPM (b) Reconstruction image

Figure 3: $SIE = 2302$ for this pair of SPM and reconstruction images.



(a) SPM (b) Reconstruction image

Figure 4: $SIE = 22,641$ for this pair of SPM and reconstruction images.

We construct a function, $SIE(\mathbb{I}, \mathbf{x})$, for the entire dataset by summing the SIE error for all pixels in image set $\mathbb{I}$.

Characteristics of $SIE(\mathbb{I}, \mathbf{x})$ are:

- Closed-form psuedo-Boolean function
- High degree for large datasets (975)
- Non-submodular

The SfIS and SfSPM reconstruction problems then become

$$\min_{\mathbf{x} \in \mathbb{B}^n} SIE(\mathbb{I}, \mathbf{x}) \quad (1)$$

5 Algorithm

To solve Eq. 1 is an NP-Complete problem because that $SIE(\mathbb{I}, \mathbf{x})$ is non-submodular, so we search for a local minimum using standard moves and a heuristic developed for SfIS and SfSPM. The process is as follows:

1. Begin with the visual hull as the initial labeling of voxels.
2. In random order, test whether each voxel's label should be changed by evaluating the partial first derivatives of $SIE(\mathbb{I}, \mathbf{x})$ and our heuristic.
3. Repeat until no voxel's label is changed in step 2.

At the conclusion of the algorithm, the current labeling is a local minimum of $SIE(\mathbb{I}, \mathbf{x})$. Our heuristic prevents the search from stalling in local minima with high values of $SIE(\mathbb{I}, \mathbf{x})$.

8 Conclusions

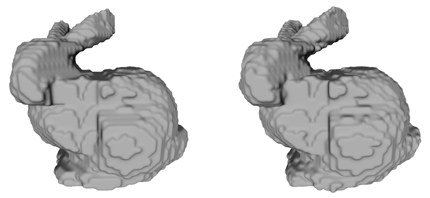
- Thin sections of the trees were reconstructed with both SfIS and SfSPM datasets despite camera calibration and silhouette error
- Our method works for thicker objects as well as thin ones
- The reconstructions using SfIS and SfSPM versions are very similar
- There is little change after the first few iterations of the algorithm

9 Future Work

Goals for future work include reducing run time, correcting camera calibration error from the reconstruction, reducing noisy regions, and identifying parts of the tree from the reconstruction.

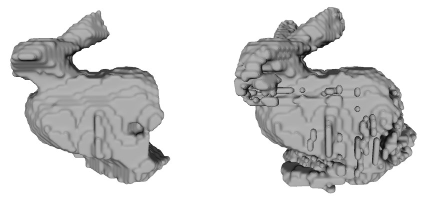
6 Synthetic dataset

The well-known Stanford bunny model was used to generate synthetic datasets with a known ground truth. (G. Turk and M. Levoy, Zippered polygon meshes from range images, in Proceedings of the 21st annual conference on Computer graphics and interactive techniques, SIGGRAPH 94, (New York, NY, USA), pp. 311318, ACM, 1994.)
There are three datasets: perfect segmentation in BUNNY-NO-ERROR, significant segmentation error in BUNNY-SEGMENTATION-ERROR, and BUNNY-IMAGE-NOISE, where there was 20% image noise.



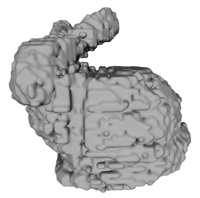
(a) VH (b) SfIS

Figure 5: BUNNY-NO-ERROR dataset: VH and SfIS reconstructions.



(a) VH (b) SfIS

Figure 6: BUNNY-SEGMENTATION-ERROR dataset: VH and SfIS reconstructions.

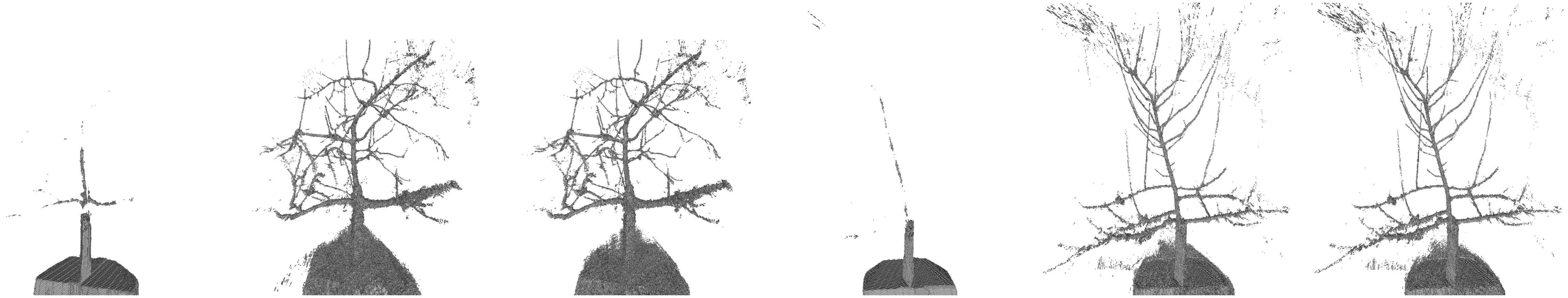


(a) VH (b) SfIS

Figure 7: BUNNY-IMAGE-NOISE dataset: VH and SfIS reconstructions.

7 Real datasets of leafless trees

We tested our algorithm on trees in the laboratory, using SfIS and SfSPM versions of the datasets generated by the same background model. The number of voxels was 54.4 million (each side of a voxel measured 3.6 mm) and 30 cameras were used. Run time was 16-40 minutes, depending on the dataset.



(a) TreeB:VH (b) TreeB: SfIS (c) TreeB: SfSPM (d) TreeC: VH (e) TreeC: SfIS (f) TreeC: SfSPM

Figure 8: Comparison of the VH and reconstructions of SfIS and SfSPM versions of a tree dataset with our local minimum search method.