Generating 3D Point Clouds of Plants for Fusarium Head Blight Detection

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23 April 2025

Introduction

This project focuses on developing synthetic 3D point clouds of plant structures to support the detection of Fusarium Head Blight (FHB), a major disease affecting cereal crops. The main challenge lies in the scarcity of large, diverse, and high-quality datasets. Our goal was to explore generative models that could create biologically realistic synthetic data to augment real datasets. This report outlines our iterative modeling efforts—from point cloud diffusion to statistical spline modeling—highlighting the rationale, methods, failures, and outcomes at each stage.

Initial Challenge and Point Cloud Generation

Our starting point was to use a PointNet++-based diffusion model to generate 3D plant point clouds from Gaussian noise. The diffusion process would iteratively denoise samples to approximate realistic structures. However, the approach quickly encountered fundamental issues.

Traditional loss functions like Mean Squared Error (MSE)[1] and Earth Mover's Distance (EMD)[2] penalized spatial deviations too heavily. While these metrics are effective for rigid object generation, they failed in our case: two different plants may be geometrically dissimilar but biologically valid. The model received high loss even when its outputs were plant-like, simply because they did not match the specific reference point cloud.

This misalignment in supervision hindered the model's ability to converge. Many of the generated samples collapsed into trivial or indistinct shapes. Attempts to adjust the loss weights and introduce variance into target samples did not resolve the issue.

We then explored a transformer-based diffusion model to address potential limitations in spatial modeling. Transformers can, in theory, learn global relationships better than PointNet++. However, they are known to require large datasets and exhibit training instability on small, noisy data. Given our dataset of only 60 plant point clouds, the

[1] **MSE**: Measures the average squared difference between corresponding points in generated and reference data. A lower MSE indicates closer alignment in Euclidean space.

[2] **EMD**: Computes the minimum cost of transforming one distribution into another by moving mass between points. Commonly used to compare point clouds with different shapes.

transformer-based approach showed minimal improvement and was discontinued after preliminary trials.

Spline-Based Modeling: A Shift in Representation

To improve learning efficiency and capture structural regularities, we transitioned from full point clouds to parametric representations using cubic B-splines. The idea was to extract the skeleton of each plant and fit branches with four control points per spline. This low-dimensional encoding would ideally reduce the learning burden and improve generalization.

The process involved multiple steps:

- Skeletonizing 3D point clouds to identify branch-like structures.
- Clustering and separating individual branches from the skeletal graph.
- Fitting cubic B-splines with knot placement heuristics.
- Normalizing and aligning all splines to a consistent root at the origin.

This conversion pipeline went through 18 iterations. We refined curve fitting strategies, improved noise filtering, and restructured data to maintain spline consistency. Ultimately, we were able to process 55–56 of the original 60 plants into usable spline-based datasets. The remaining cases were too noisy or topologically inconsistent to recover.

Diffusion Modeling with Splines

Having established spline representations, we again attempted generative modeling. A transformer-based diffusion model was trained to generate sets of control points. The architecture was configured to support variable-length inputs via positional padding.

Despite the reduced complexity, training remained unstable. The dataset was still small, and spline-based losses (again using MSE, EMD, and Chamfer Distance[3]) were not expressive enough. These losses focused on spatial proximity, not structural plausibility. Generated splines exhibited irregular bending, unnatural curvature, or complete degeneration. The transformer failed to learn consistent patterns in the distribution of control points.

We hypothesized that the lack of high-quality loss functions and the still-too-small dataset size made the approach unfeasible. Introducing rule-based losses or augmenting the spline dataset might help, but we chose to explore a new direction instead.

[3]**Chamfer Distance**: Calculates the average nearest-neighbor distance between points in two point sets, summing the distances from each point to its closest counterpart. Often used in 3D shape generation tasks.

A Statistical Alternative: Gaussian Sampling and Fuzzy Filtering

We pivoted to a statistical modeling approach. Using the control points of the fitted splines, we computed a multivariate Gaussian distribution across all branches. This allowed us to generate new samples simply by sampling from the distribution and reshaping into control point sets.

However, raw sampling from the Gaussian often yielded unrealistic branches. To address this, we introduced fuzzy filtering based on biologically inspired constraints:

- **Curvature Rule:** Branches had to exhibit realistic drooping or arching.
- **Symmetry Check:** Branch midpoints were compared to ensure axial balance.
- **Height Threshold:** Drooping branches needed sufficient downward displacement.
- **Bending Exclusion:** Branches showing reversal or kinks were discarded.

We also centered every plant by translating its root to the origin. This normalized the coordinate space, making control points more consistent and reducing variance in the data.

This method proved highly effective. Approximately 40–50% of generated branches passed all fuzzy criteria, and visual inspection confirmed that many were highly plant-like. Though not as expressive as a learned generative model, this approach was simple, robust, and tunable.

Future Work: Spline-to-Point Cloud and Perceptual Losses

One pending objective is to convert splines back into dense point clouds. This would enable compatibility with point-based classifiers and allow direct visualizations. While uniform sampling is straightforward, it does not preserve fine structure such as branch tip detail. Future methods may use adaptive sampling or curvature-weighted techniques.

Another major improvement would involve perceptual loss functions. Instead of using point-wise distances, a loss network trained to recognize plant features (e.g., via convolutional or graph neural networks) could evaluate the plausibility of outputs. A promising candidate is the Fréchet Inception Distance (FID)[4], extended to 3D feature space. Such a metric would compare the distribution of learned embeddings rather than geometric coordinates.

Integrating these components could enable an end-to-end pipeline: generate spline control points, validate via fuzzy logic or FID, convert to point clouds, and use the results for downstream tasks.

[4] **Fréchet Inception Distance (FID)**: Measures how close the distribution of generated features is to that of real data, using the mean and covariance of learned representations (typically extracted from a neural network). Lower values indicate greater similarity.

Conclusion

This project illustrates the challenges of generating 3D plant structures from limited data. PointNet++ and transformer-based diffusion models proved inadequate under current conditions, primarily due to loss function limitations and data scarcity. The shift to spline modeling, followed by Gaussian sampling and fuzzy filtering, enabled effective generation of biologically plausible structures.

The final pipeline produces synthetic branches that capture the visual and geometric qualities of real plants. These outputs can be used for training classifiers, simulating plant growth, or testing disease detection pipelines. With further refinement, especially in loss design and point cloud reconstruction, this framework offers a strong foundation for data-driven plant modeling.

References

[1] Luo, S., & Hu, W. (2021). *Diffusion Probabilistic Models for 3D Point Cloud Generation.* arXiv preprint arXiv:2103.01458.