Uncracking the Bagel One Crumb at a Time

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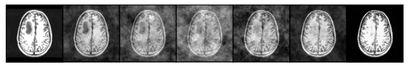
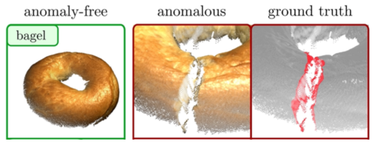
Motivation

- Anomaly detection with 2D datasets with Denoising Diffusion Probabilistic Models (DDPMs) for unsupervised anomaly detection [1]



- Lack of a comprehensive 3D anomaly dataset
  - not many applications of unsupervised anomaly detection and localization in the 3D domain.
  - the first comprehensive 3D dataset for this purpose: MVTec3D-AD Dataset [2]



Contribution

- To address the limitations of low quality generation results in the 3D space → Point Voxel Diffusion
- **Goal :** use Point Voxel Diffusion to find the anomaly in bagels (a category in the MVTec 3D-AD Dataset)

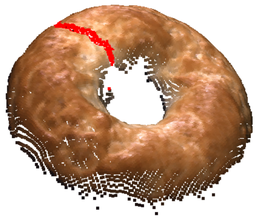
Outcomes

- Compared to other baseline methods: Voxel GAN, Voxel AE, Voxel VM → higher performance with our architecture
  - SOTA for 3D anomaly detection with voxels

Approach

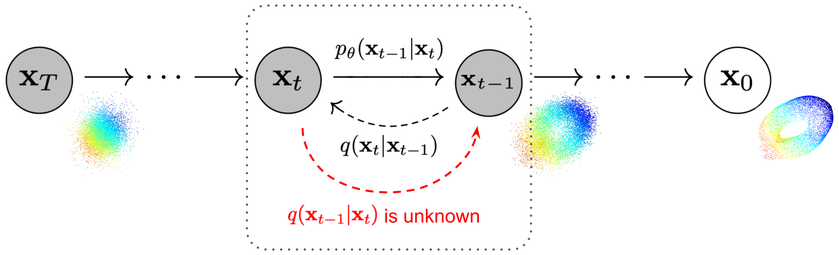
1. Preprocessing Pipeline

- RANSAC [3] applied on the point cloud → remove the background plane.
- Outliers are removed via a connected-component-based algorithm.
- The resulting point cloud contains a large number of zero points because of the original background pixels → remove them from the input data.
- Compute the mean and standard deviation of points on the training and validation data
- Perform normalization on the input point clouds.



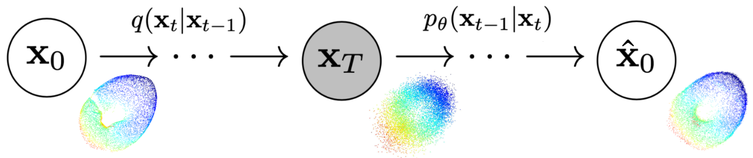
2. Shape Generation (Training)

- Train the model for shape generation → learn a distribution of healthy samples.
- Sample N points from a training example → passed as input to the model



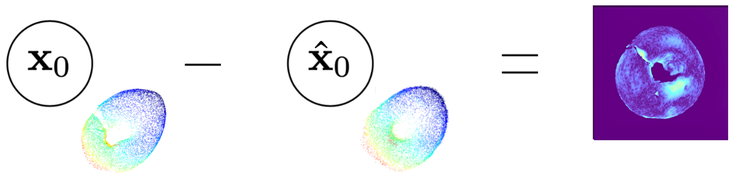
3. Anomaly Detection (Inference)

- Add noise to the point cloud for T timesteps
- Denoise the point cloud
- Compare the original point cloud with the denoised one to find the anomaly

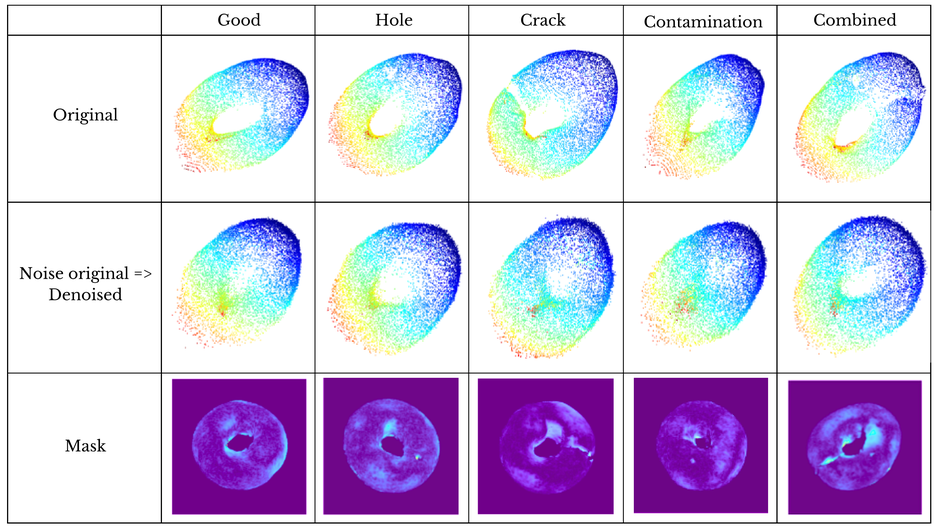


4. Masks

- Take ground truth point cloud → target width and target height
- Take the anomalous point cloud
- Calculate the distance between the two point clouds using Chamfer Distance
- Predict anomaly mask
  - size → target width and target height
  - create the mask using the values from the Chamfer Distance calculation

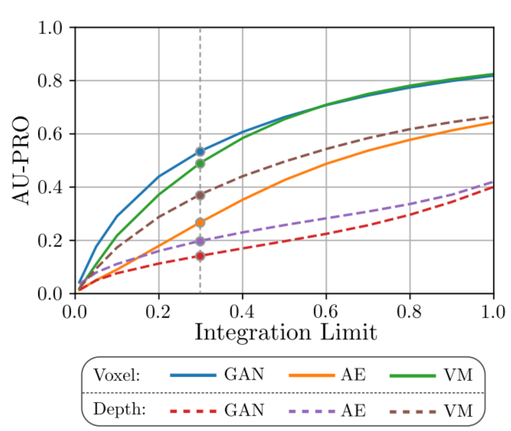


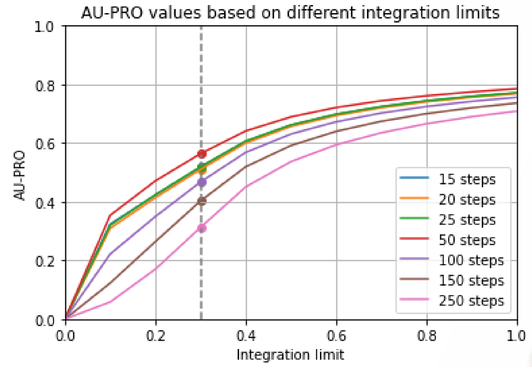
Qualitative Results



Original Point Cloud → Noise for 50 steps → Denoise for 50 steps → Anomaly Detection using Masking

Quantitative Results





- AU-PRO → Area Under Per-Region Overlap → baseline for anomaly algorithms
- Integrating to a false positive rate of 0.3 → score of 0.563 which outperforms the current benchmark (0.453)

set of pixels predicted as anomalous for a threshold

set of pixels marked as anomalous for k in i

$$\mathrm{PRO} = \frac{1}{N}\sum_i \sum_k \frac{|P_i \cap C_{i,k}|}{|C_{i,k}|}$$

ground truth image i

component k

Method	AU-PRO Score Limit = 0.3
Voxel GAN	0.440
Voxel AE	0.260
Voxel VM	0.453
Ours	**0.563**

#SOTA results

References

[1] J. Wyatt, A. Leach, S. M. Schmon, and C. G. Willcocks, 'Anoddpm: Anomaly detection with denoising diffusion probabilistic models using simplex noise', in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 650–656.

[2] P. Bergmann, X. Jin, D. Sattlegger, and C. Steger, 'The mvtec 3d-ad dataset for unsupervised 3d anomaly detection and localization', *arXiv preprint arXiv:2112. 09045*, 2021.

[3] K. G. Derpanis, 'Overview of the RANSAC Algorithm', Image Rochester NY, vol. 4, no. 1, pp. 2–3, 2010.