3DPointGAN: Point Cloud Denoising Using MLP Based GAN

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Introduction

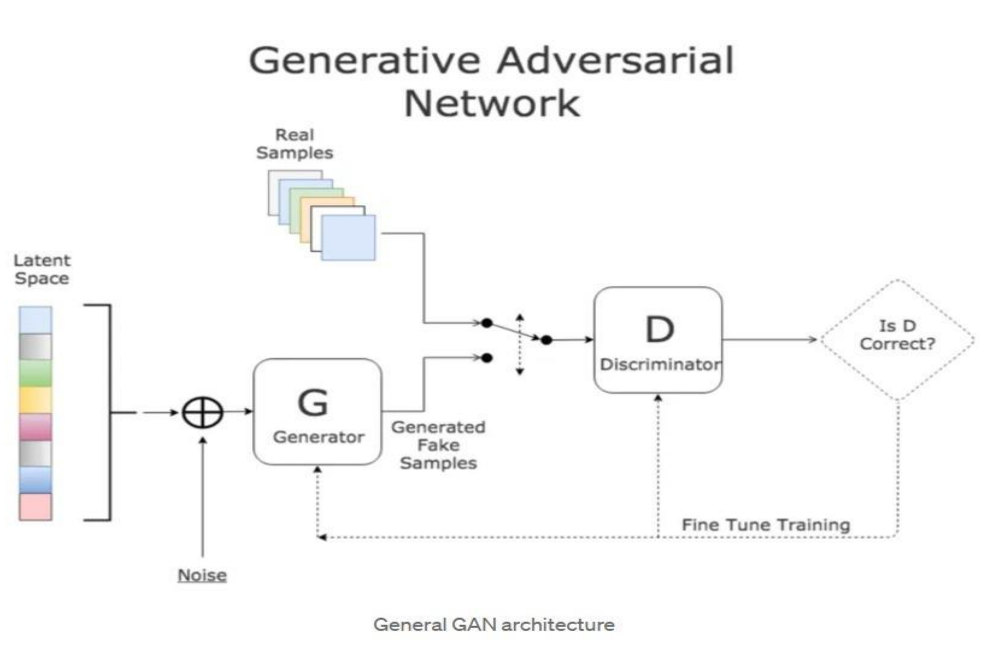
- A 3D point cloud is a collection of points in 3D space, representing the geometry of objects or environments using spatial coordinates .
- Point clouds often suffer from noise, making denoising critical for accurate and reliable downstream processing.
- Reducing noise enhances the quality, reliability, and usability of 3D point clouds in real-world applications.
- We propose developing a GAN-based framework to effectively denoise 3D point clouds by leveraging the generator-discriminator architecture to remove noise while preserving the geometric structure .

Existing Work

- Techniques like local surface fitting and statistical filtering have been widely used but struggle with complex noise models, limiting their effectiveness .
- Score-Based-Denoising estimates the gradient of the log-probability and iteratively updates noisy points using gradient ascent, achieving significant noise reduction while preserving structure.
- A novel method using Diffusion Schrödinger bridges to map noisy to clean point clouds, outperforming existing methods on datasets like PU-Net and ScanNet++. Incorporating features like color and DINOv2 further enhances performance.
- .Denoising GANs for images are used to produce high quality images (32 spp) from low quality samples (4/8 spp), to greatly reduce rendering times.

Generative Adversarial Networks

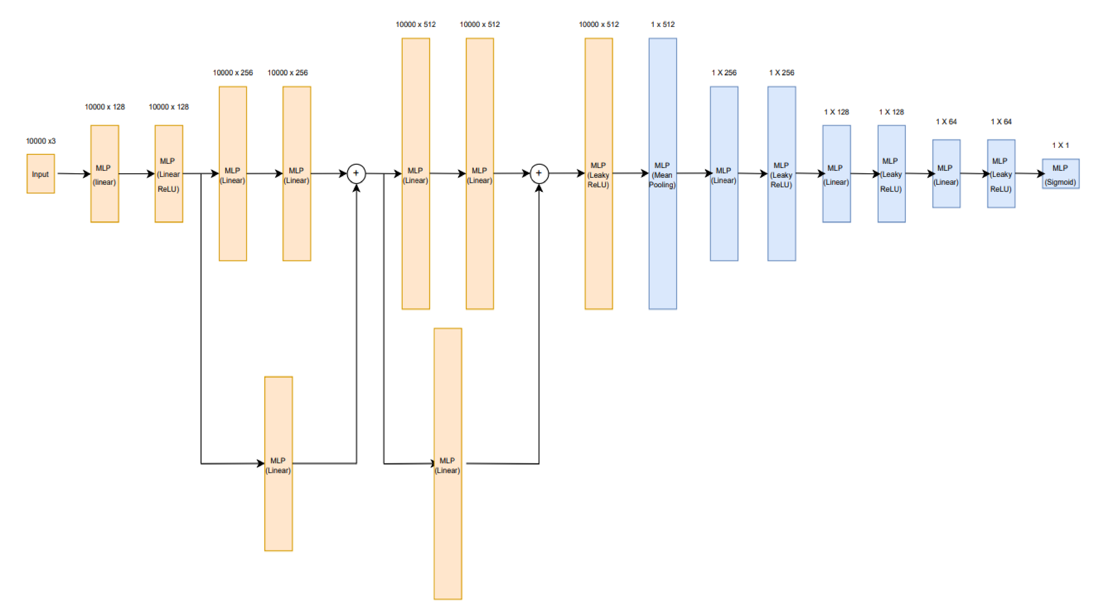
- Generative Adversarial Networks (GANs) are deep learning models used to generate realistic data similar to a given dataset.
- Consists of two neural networks generator and discriminator. Generator creates fake data to mimic the real dataset. Discriminator evaluates data and distinguishes between real and fake samples.
- The generator learns to create increasingly realistic fake data.
- The discriminator learns to identify fake data more accurately.
- Both networks are trained together in a competitive setup, improving until the generator produces data that is almost indistinguishable from the real data.



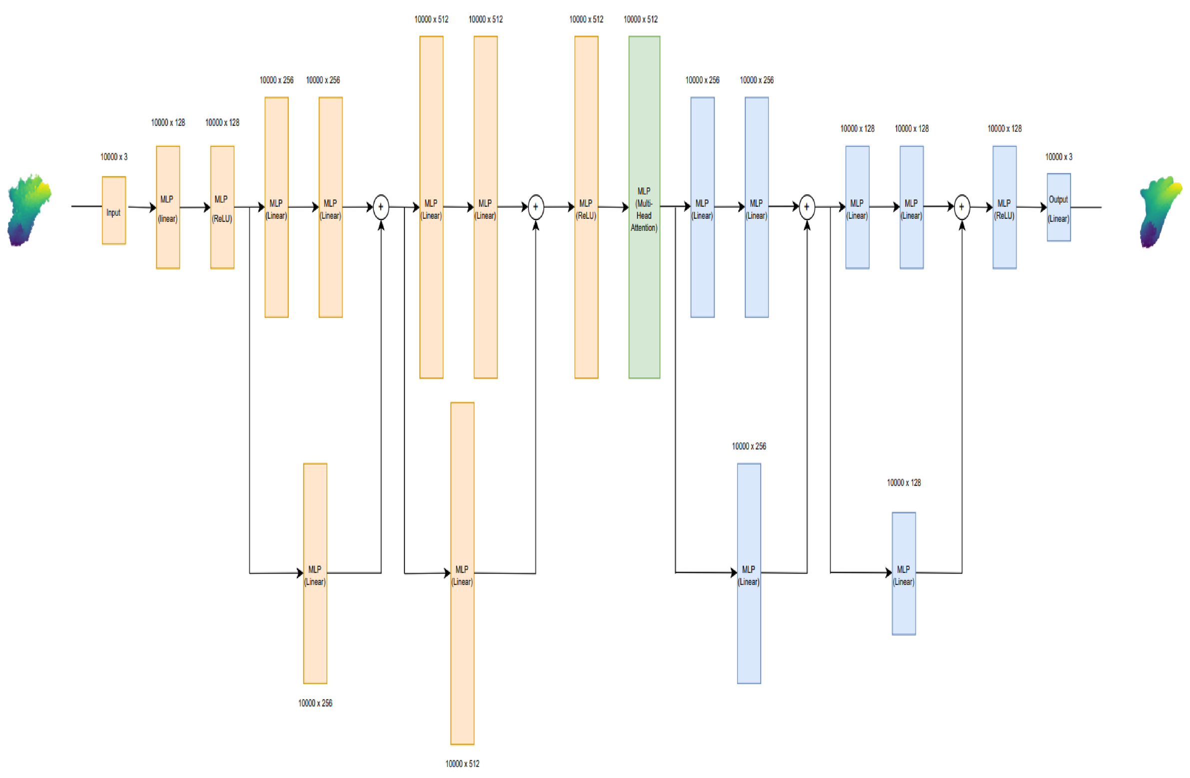
- GANs can perform point cloud denoising by training the generator to reconstruct clean point clouds from noisy inputs while the discriminator ensures the output resembles real, noise-free data. Through this adversarial training, the generator learns to remove noise and restore the underlying structure of the point cloud.

Our Approach

- We developed a GAN-based framework for 3D point cloud denoising, consisting of Generator and Discriminator networks
- Generator Network features an encoder-decoder architecture with residual blocks to learn robust feature representations.
- Incorporates a multi-head attention mechanism to capture spatial dependencies and improve denoising performance.



Discriminator architecture

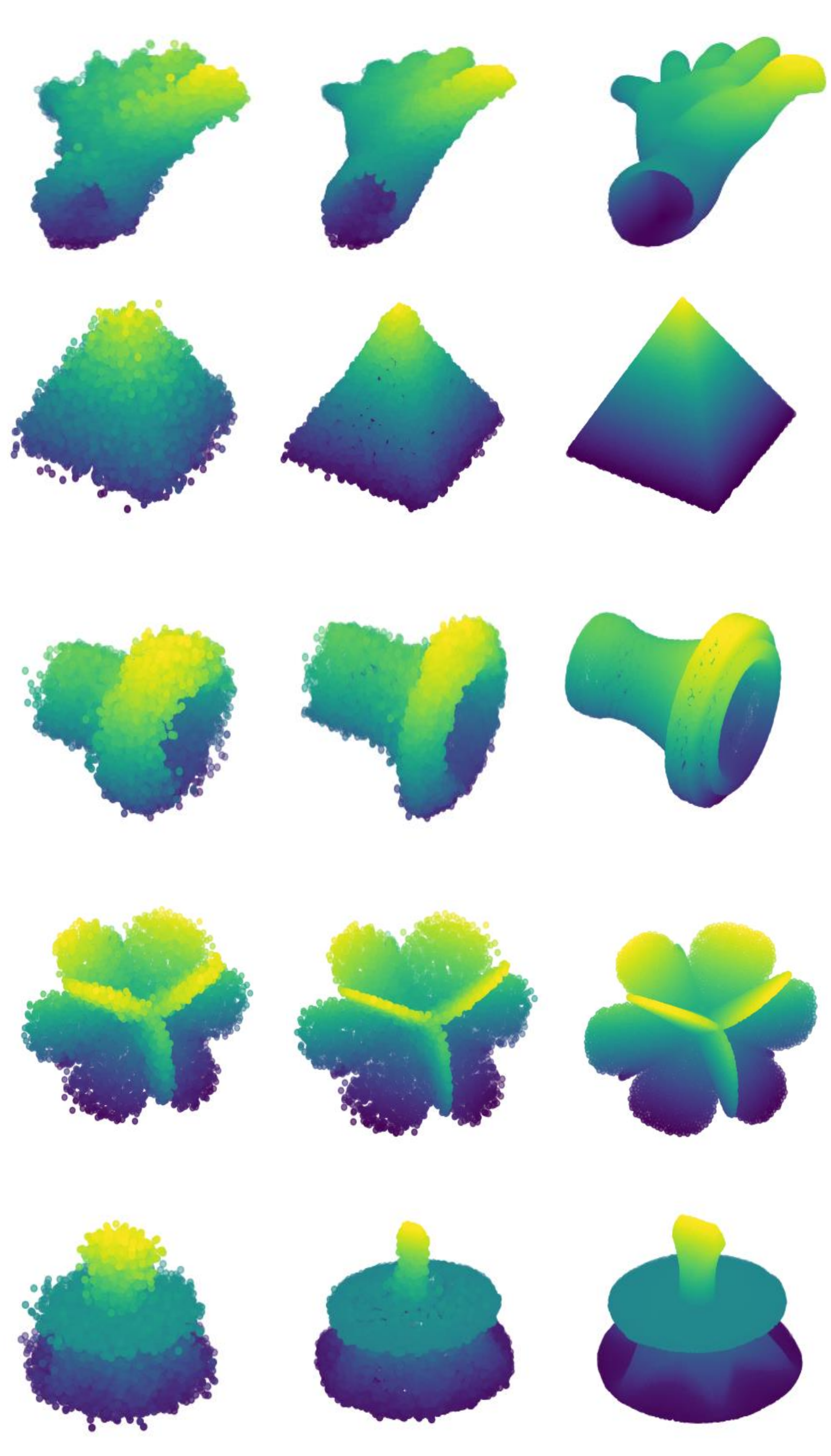


Generator architecture

- Discriminator Network extracts local point features through residual blocks and evaluates them through a fully connected network to distinguish between real and generated point clouds.
- Training Process uses adversarial loss to encourage realistic outputs from the generator, and an additional L1 loss to ensure geometric accuracy. Both networks are optimized using Adam optimizers for stable and effective training.

Experimentation

Noisy | **Denoised** | **Clean**



Results

Sigma	Chamfer Distance	Point to Face Distance
0.01	6.8	5.9
0.02	7.6	6.8
0.03	8.3	7.7

All these values are after multiplying with 10^4 .

$$\text{Chamfer Distance}(A, B) = \frac{1}{|B|}\sum_{b\in B}\min_{a\in A}\|a-b\|^2 + \frac{1}{|A|}\sum_{a\in A}\min_{b\in B}\|a-b\|^2$$

$$\text{P2F Distance}(A, B) = \frac{1}{|A|}\sum_{a\in A}\min_{b\in B}\|a-b\|^2$$

- Our approach delivered remarkable results, demonstrating significant improvements in accuracy and quality. While it did not surpass the state-of-the-art methods, it showcased competitive performance.
- The GAN maintains good denoising performance even if noise levels (σ) tripled from 0.01 to 0.03, showing less degradation in reconstruction quality.
- Correlation between Chamfer and Point-to-Face distances across different noise levels indicates stable geometric reconstruction.

Future Prospects and Applications

- Fine-tuning the network architecture, including the size and number of layers, to improve the model's ability to capture finer geometric details and handle varying noise levels effectively.
- Introducing additional diffusion steps during training to make the GAN more robust against diverse and complex noise distributions, ensuring better generalization across different datasets.
- Expanding the framework to denoise point clouds in cross-domain scenarios, such as medical imaging or aerial mapping, to demonstrate its versatility and adaptability to domain-specific challenges.

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