Multi-Scale Point Cloud Completion Networks Incorporating Attention Mechanisms

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Abstract

Point cloud completion, a critical task in 3D vision, aims to repair incomplete point cloud data caused by sensor limitations or environmental occlusions, thereby providing complete 3D structural information for downstream applications. Most existing methods employ global generation strategies to directly output complete point clouds, but these approaches frequently alter the original geometric structures, resulting in detail loss or increased noise. A novel attention-based multi-scale point cloud completion network is proposed to overcome these limitations. The first enhancement introduces a channel attention mechanism during multi-scale feature fusion, which strengthens the coordinated expression of local details and global semantics through adaptive weight allocation. The second improvement designs a hybrid loss function that combines Wasserstein GAN with gradient penalty and geometric consistency constraints, thereby enhancing both detail authenticity and structural coherence in generated point clouds. Experiments conducted on the ShapeNet-Part dataset demonstrate the effectiveness of the proposed method. The improved approach achieves a reduction in Chamfer Distance compared to PF-Net, with particularly enhanced robustness observed in completing complex structures such as hollow chair backs and thin-walled lampshades. These results validate the superiority of the proposed technical innovations in geometric detail preservation and structural integrity maintenance.

1. Introduction

Three-dimensional point cloud completion technology represents a crucial research direction in computer vision and 3D reconstruction, aiming to algorithmically repair incomplete point cloud data caused by sensor limitations or environmental occlusions to restore complete geometric structures of objects. With rapid advancements in autonomous driving, robotic navigation, and augmented reality applications, the demand for high-precision 3D environmental perception has become increasingly urgent (Pham et al., 2021). For instance, in autonomous driving scenarios, LiDAR-captured point clouds often exhibit partial missing regions due to vehicle occlusions or complex weather conditions. Direct utilization of such data for obstacle detection or path planning may lead to critical safety risks. Traditional point cloud completion methods predominantly rely on handcrafted geometric interpolation algorithms, such as Poisson reconstruction or surface fitting. However, these approaches frequently underperform when handling complex topological structures or large-scale missing regions, while also struggling to generalize across diverse object categories (Huang et al., 2020).

Recent breakthroughs in deep learning have provided new perspectives for point cloud processing. Early works like PointNet (Charles et al., 2017) and PointNet++ (Qi et al., 2017) demonstrated the potential of neural networks in point cloud classification and segmentation tasks by directly processing unordered point sets. Building upon these foundations, point cloud completion methods have gradually shifted from voxelization or multi-view projection to end-to-end point cloud generation. For example, PCN (Point Completion Network) (Yuan et al., 2018) employs an encoder-decoder architecture to generate complete point clouds through folding operations that map 2D grids to 3D space. However, its global generation strategy tends to overwrite original point clouds, thereby distorting the geometric structures of input regions. Although FoldingNet (Yang et al., 2018) optimizes the generation process, it still faces challenges in detail blurring and noise accumulation. PF-Net (Point Fractal Network) (Huang et al., 2020) introduces an innovative partial generation framework that predicts only missing regions rather than entire point clouds, effectively preserving the original input structures. Nevertheless, PF-Net adopts simplistic feature concatenation for multi-scale feature fusion, failing to fully exploit semantic relationships across multi-resolution features. Additionally, its adversarial loss design remains overly simplistic, limiting the diversity and geometric authenticity of generated results.

Specifically, PF-Net's limitations manifest in two aspects. First, the feature fusion stage neglects the importance differences among channels, allowing high-dimensional features to potentially obscure critical low-level geometric details. Second, the adversarial loss relies solely on a binary classification discriminator, inadequately constraining surface smoothness and local consistency in generated point clouds. These issues become particularly pronounced in complex scenarios. For instance, when completing a chair with hollow backrest structures, existing methods may erroneously fill cavity regions or generate incoherent support structures.

To address these challenges, this paper proposes an improved framework based on PF-Net, with two core contributions. First, a channel attention mechanism dynamically adjusts fusion weights of multi-scale features, enhancing the network's collaborative perception of local details and global semantics. Second, a hybrid loss function combines Wasserstein GAN with gradient penalty (WGAN-GP) (Zhang et al., 2019) and normal vector consistency constraints, simultaneously improving generation diversity and geometric rationality. Experiments demonstrate that the proposed method significantly reduces Chamfer Distance errors on the ShapeNet-Part dataset and exhibits superior detail restoration capabilities in complex structure completion tasks. This work not only provides a new

technical pathway for point cloud completion but also offers reliable solutions for 3D perception challenges in practical applications such as autonomous driving and industrial inspection.

2. Related work

Three-dimensional point cloud completion technology represents a crucial research direction in computer vision and 3D reconstruction, aiming to algorithmically repair incomplete point cloud data caused by sensor limitations or environmental occlusions to restore complete geometric structures of objects. With rapid advancements in autonomous driving, robotic navigation, and augmented reality applications, the demand for high-precision 3D environmental perception has become increasingly urgent. For instance, in autonomous driving scenarios, LiDAR-captured point clouds often exhibit partial missing regions due to vehicle occlusions or complex weather conditions. Direct utilization of such data for obstacle detection or path planning may lead to critical safety risks. Traditional point cloud completion methods predominantly rely on handcrafted geometric interpolation algorithms, such as Poisson reconstruction or surface fitting. However, these approaches frequently underperform when handling complex topological structures or large-scale missing regions, while also struggling to generalize across diverse object categories.

Recent advancements in deep learning have significantly propelled research progress in point cloud completion, with existing methods broadly categorized into voxel-based, global generation, and partial generation approaches. Early works convert point clouds into voxel grids for completion using 3D convolutional networks, but face limitations in resolution and computational efficiency. The emergence of PointNet (Charles et al., 2017) shifted focus to direct point cloud processing. PCN (Yuan et al., 2018) employs an encoder-decoder framework with folding operations to generate complete point clouds, yet its global generation strategy tends to overwrite original structures, causing detail loss (Li et al., 2023). FoldingNet (Yang et al., 2018) further optimizes surface reconstruction but exhibits limited adaptability to complex topological structures. Partial generation methods like PF-Net (Huang et al., 2020) preserve known structures by hierarchically predicting missing regions, yet rely on simplistic concatenation for multi-scale feature fusion, failing to fully explore inter-channel correlations. Multi-scale feature fusion techniques have been widely applied in multimodal tasks. PointNet++ (Qi et al., 2017) extracts local features through hierarchical sampling and grouping, but its inter-level information transmission depends on fixed rules (Huang et al., 2020). MSN proposes a multi-resolution tree network to fuse features of varying granularity, yet lacks adaptive weighting mechanisms. Recently, Transformer architectures have been introduced to point cloud processing. PoinTr (Yu et al., 2021) models global context via self-attention but suffers from high computational complexity and insufficient focus on local details.

3. Method

The proposed framework builds upon PF-Net, retaining its core architecture of multi-resolution encoder (MRE) and point pyramid decoder (PPD) (Huang et al., 2020), while optimizing multi-scale feature fusion and loss function design. Key improvements include a multi-scale channel attention mechanism and a hybrid loss function, aiming to enhance local detail perception and improve geometric consistency and diversity in generated point clouds.

The development of attention mechanisms in 3D tasks offers new insights for point cloud completion. PointTransformer enhances semantic understanding in classification and segmentation through self-attention. CAE-Net (Mahmud et al., 2024) introduces channel attention for feature selection in completion tasks, but its attention module operates only on single-scale features. In contrast, the proposed multi-scale channel attention mechanism achieves balanced integration of local details and global semantics through hierarchical weighted fusion, addressing limitations of existing methods.

Generative Adversarial Networks (GANs) and their variants demonstrate strong performance in point cloud generation. L-GAN pioneers GAN applications for point cloud generation but produces coarse results. Subsequent works like 3D-PointCapsule enhance generation diversity via capsule networks but exhibit limited capability in modeling complex geometric structures. Wasserstein GAN with gradient penalty (WGAN-GP) (Zhang et al., 2019) improves training stability through Lipschitz constraints and effectively mitigates mode collapse, yet remains underutilized in point cloud completion. This work integrates WGAN-GP with geometric consistency losses to enhance generation diversity while constraining local surface smoothness.

Regarding geometric constraints, existing methods predominantly rely on Chamfer Distance (CD) or Earth Mover's Distance (EMD) to measure point cloud similarity, but such metrics struggle to capture local geometric properties. Recent works like propose normal vector consistency losses to enhance geometric plausibility by aligning surface orientations between generated and ground-truth point clouds. introduces curvature consistency losses to optimize complex surface generation. Building on these, a hybrid loss function is designed to combine global shape matching with local curvature continuity constraints, improving the physical plausibility of completion results.

In summary, while existing methods have achieved progress in point cloud completion, limitations persist in adaptive multi-scale feature fusion, balance between generation diversity and geometric consistency, and dynamic feature selection. This work addresses these challenges by proposing an optimized framework integrating channel attention mechanisms, hybrid loss functions, and dynamic sampling, offering a more efficient solution for complex point cloud completion tasks.

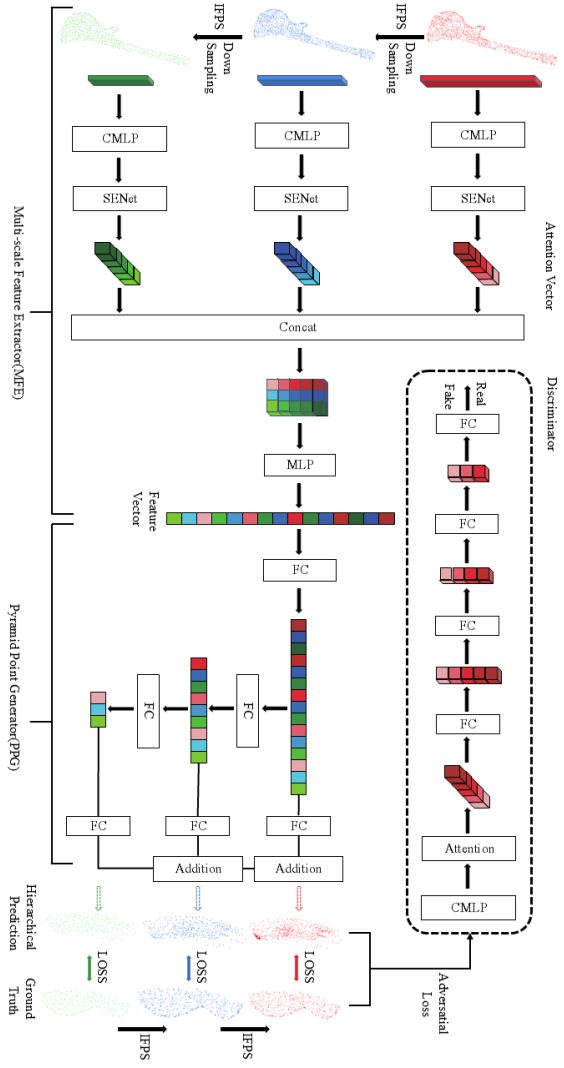

Figure 1. The framework of a multi-scale point cloud completion network integrating attention mechanisms.

3.1 Multi-scale Channel Attention Mechanism

The proposed framework builds upon PF-Net, retaining its core architecture of multi-resolution encoder (MRE) and point pyramid decoder (PPD) (Huang et al., 2020), while optimizing multi-scale feature fusion and loss function design. Key improvements include a multi-scale channel attention mechanism and a hybrid loss function, aiming to enhance local detail perception and improve geometric consistency and diversity in generated point clouds.

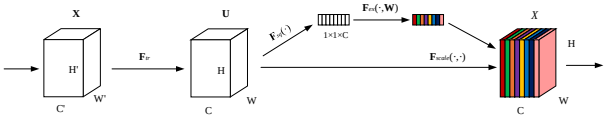

Figure 2. A Squeeze-and-Excitation block.

Traditional PF-Net extracts multi-scale features via MRE but relies on simple concatenation for feature fusion, neglecting importance variations among channels in semantic representation. For example, in chair completion tasks, high-frequency detail features (e.g., edge points) dominate the support structures of chair backs, while low-frequency global features determine the overall shape of chair seats. To adaptively enhance critical channel expressiveness, a channel attention module is introduced. The design draws inspiration from the Squeeze-and-Excitation Network (Hu et al., 2018), but adapts to the unstructured nature of point clouds. Figure 2 illustrates the core workflow of the SE module. The SE module first applies Global Average Pooling (GAP) to input features, compressing spatial dimensions into channel-wise descriptors (Squeeze operation). Subsequent processing involves two fully connected layers that learn nonlinear inter-channel relationships (Excitation operation). Unlike the original SENet, the CMLP module (as shown in Figure 3) employs a parameter-sharing network to handle multi-scale features during channel weight generation. Enforced cross-level parameter reuse strengthens geometric correlations between features at different resolutions. This architectural modification enhances information interaction across hierarchical representations while maintaining computational efficiency.

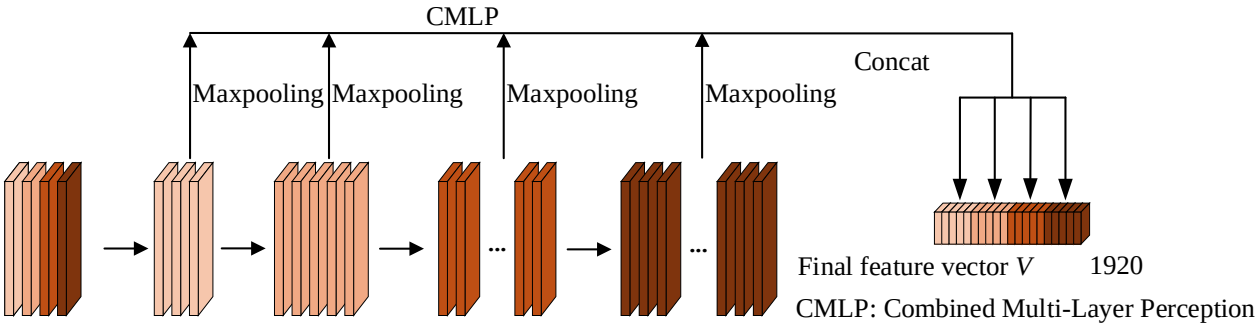

Figure 3. The feature extractors of 3Dpoint encoders.

Specifically, for multi-scale features $\{F_1, F_2, F_3, F_4\}$ (dimensions: 128, 256, 512, 1024) output by the CMLP module in MRE, global average pooling (GAP) compresses spatial information into channel descriptors:

$$z_i = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} F_i(h, w) \tag{1}$$

where $H \times W$ denotes spatial dimensions of feature maps. This operation captures global channel statistics, such as point density in chair back regions or local curvature distributions. A two-layer fully connected network then learns nonlinear inter-channel relationships and outputs normalized weight vectors:

$$s_i = \sigma\left(W_2 \cdot \delta\left(W_1 \cdot z_i\right)\right) \tag{2}$$

where $W_1 = \mathbb{R}^{C/r \times C}$ and $W_2 = \mathbb{R}^{C \times C/r}$ are learnable parameters, $r = 16$ represents the compression ratio, δ denotes the ReLU activation, and σ signifies the Sigmoid function. Original features undergo dynamic adjustment through channel-wise multiplication:

$$\tilde{F}_i = s_i \odot F_i \tag{3}$$

In the formula, $\odot$ represents the multiplication of each channel. This design enables adaptive enhancement of channel features strongly correlated with missing geometric structures. For instance, when completing hollow chair backs, weights for high-frequency detail channels (e.g., edge orientations) increase significantly, while weights for low-frequency global channels (e.g., overall symmetry) decrease relatively.

During decoding, the PPD further optimizes generation through hierarchical attention mechanisms. The primary layer generates low-resolution skeleton points, with attention weights computed via graph convolutional network (GCN) (Liu et al., 2022) :

$$\alpha_j = Softmax\left(\mathrm{q}^T \cdot \phi\left(y_j\right)\right) \tag{4}$$

where ϕ represents the local geometric features extracted by GCN, q is the learnable query vector, and α_j indicates the attention score of the j -th skeleton point. The secondary layer fuses primary-layer features with current-layer features through cross-attention:

$$Y_{secondary} = \sum_k \beta_k \cdot \psi\left(y_k^{primary} \oplus y_k^{current}\right) \tag{5}$$

where β_k represents the attention weight, $\oplus$ indicates feature concatenation, and ψ is the multi-layer perceptron (MLP). The detail layer introduces joint spatial-channel attention by extracting local geometric contexts via 3D convolution and computing spatial attention maps:

$$A_{spatial} = Sigmoid\left(C\mathrm{onv3D}\left(Y_{\mathrm{detail}}\right)\right) \tag{6}$$

Final detailed point clouds are generated through combined spatial-channel attention:

$$Y_{detail} = A_{spatial} \odot \left(A_{\mathrm{channel}} \odot F_{detail}\right) \tag{7}$$

This hierarchical design enables progressive refinement of missing geometric structures while preserving spatial coherence with original point clouds. For example, chair leg completion involves skeleton point generation in the primary layer, structural refinement in the secondary layer, and surface texture supplementation in the detail layer.

3.2 Hybrid Loss Function

The proposed framework builds upon PF-Net, retaining its core architecture of multi-resolution encoder (MRE) and point pyramid decoder (PPD), while optimizing multi-scale feature fusion and loss function design. Key improvements include a multi-scale channel attention mechanism and a hybrid loss function, aiming to enhance local detail perception and improve geometric consistency and diversity in generated point clouds.

The original multi-stage Chamfer Distance (CD) loss in PF-Net effectively constrains global shape matching but exhibits limited capability in modeling local geometric details (e.g., curvature, surface smoothness). A hybrid loss function combining adversarial loss and geometric consistency constraints is proposed, comprising three components:

Dynamically Weighted Multi-stage CD Loss: The hierarchical CD constraints from PF-Net are retained but enhanced with a dynamic weight adjustment strategy. For primary, secondary, and detail generation layers, the loss function is defined as:

$$L_{CD} = \sum_{i=1}^{3} \gamma_i \cdot d_{CD}\left(Y_i, Y_{gt}^{(i)}\right) \tag{8}$$

where γ_i represents dynamic weights adaptively adjusted based on the complexity of missing regions during training. For example, weights for the detail layer (γ_3) increase for complex hollow structures (e.g., chair back meshes) to strengthen local optimization, while weights decrease for smooth surfaces (e.g., tabletops) to avoid overfitting.

Wasserstein GAN with Gradient Penalty (WGAN-GP) (Zhang et al., 2019) : To address mode collapse in traditional GAN training, WGAN-GP is adopted as the adversarial loss. The discriminator D , constructed with multi-layer graph convolutional networks (GCNs) (Liu et al., 2022) , has its loss function defined as:

$$L_{adv} = E_{\tilde{Y}\sim P_{real}}\left[D(Y)\right] - E_{\tilde{Y}\sim P_{fake}}\left[D(Y)\right] + \lambda_{\mathrm{gp}} \cdot E_{\hat{Y}\sim P_{inter}}\left[\left(\left\|\nabla_{\hat{Y}} D\left(\hat{Y}\right)\right\|_2 - 1\right)^2\right] \tag{9}$$

The generator minimizes $-E\left[D\left(\hat{Y}\right)\right]$. The gradient penalty term ($\lambda_{gp} = 10$) enforces Lipschitz continuity of the discriminator, improving training stability. Experiments demonstrate that this design significantly reduces holes and fractures in thin-walled structures (e.g., lampshades).

Normal Vector Consistency Loss: To enhance local surface smoothness, normal vector differences between generated and ground-truth point clouds are calculated. Local normals n_i are estimated via principal component analysis (PCA), with the loss defined as:

$$L_{normal} = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{n_i^{pred} \cdot n_i^{gt}}{\left\|n_i^{pred}\right\| \cdot \left\|n_i^{gt}\right\|}\right) \tag{10}$$

This loss enforces consistency in local curvature between generated and real data, particularly improving edge and hole regions. When completing the chair legs, the normal vector constraint can prevent the generated point cloud surface from having unreasonable concavities or fractures.

The total loss function combines these components as a weighted sum:

$$L_{total} = \lambda_1 L_{CD} + \lambda_2 L_{adv} + \lambda_3 L_{normal} \tag{11}$$

Optimal weights ($\lambda_1 = 1.0$, $\lambda_2 = 0.1$, $\lambda_3 = 0.5$) are determined through grid search. The training process prioritizes shape matching in early stages and gradually shifts focus to geometric detail refinement.

4. Experiment and evaluation

To train the proposed model and comprehensively evaluate point cloud completion performance, the following experiments are designed. The experiments utilize 13 categories of object shapes from the ShapeNet dataset (e.g., bags, cars, chairs, lamps) for training and evaluation. A total of 14,473 3D object point cloud models are included, with 11,705 samples allocated to the training set and 2,768 samples to the test set. All input point clouds are centered at the origin, and their 3D coordinates are normalized to the range [-1, 1]. Complete ground-truth point clouds are generated by uniformly sampling 2,048 points from the dataset models. Incomplete point clouds are created by randomly selecting one of five predefined viewpoints along the

coordinate axes and removing points within a specified radius from the selected viewpoint. The experiments employ the PyTorch deep learning platform and use the adaptive moment estimation (Adam) optimizer to train the 3D point cloud completion network. The learning rate is set to 0.0003, with a batch size of 64, and training proceeds for 201 epochs. Point cloud data with a missing ratio of 25% are used for both training and testing. Comparative evaluations with other point cloud completion methods are conducted under this configuration.

The Chamfer Distance (CD), a widely used evaluation metric in point cloud completion and 3D reconstruction, comprehensively measures geometric consistency and coverage between predicted and ground-truth point clouds through bidirectional distance calculations (Li et al., 2023). This work adopts CD as the completion evaluation metric and reports it in two components: Pred→Gt (prediction to ground truth) and Gt→Pred (ground truth to prediction). The Pred → Gt value represents the average squared distance from each point in the predicted point cloud to its nearest neighbor in the ground-truth point cloud, quantifying deviations between generated and actual point distributions. The Gt→Pred value denotes the average squared distance from each ground-truth point to its nearest neighbor in the predicted point cloud, measuring the coverage completeness of generated results. Lower values indicate better completion quality, with all values scaled by 1000 and rounded to three significant digits.

As shown in Table 1, the proposed algorithm achieves superior average CD values across 13 categories in the ShapeNet dataset compared to PF-Net and other baselines, demonstrating a 3.73% performance improvement over PF-Net. Specifically, the algorithm achieves lower CD values for seven object categories (e.g., hats, chairs) due to its attention mechanism, which better captures inter-point correlations than the CMLP structure in PF-Net. This design prioritizes the generation of critical geometric structures rather than merely minimizing CD distances to ground-truth data.

Figure 2 visualizes completion results of the proposed algorithm and PF-Net on selected ShapeNet categories. The visualization highlights the proposed method's advantages in the following aspects:

1) Precise Reconstruction Capability for Complex Structures
The proposed algorithm demonstrates enhanced geometric feature capture for objects with specialized structures. Taking the table category as an example, when the original point cloud retains only a partial segment of the footrest crossbeam, PF-Net successfully completes the main tabletop structure but fails to reconstruct the crossbeam feature. In contrast, the proposed algorithm fully restores the tabletop while accurately inferring and reconstructing the complete crossbeam morphology based on residual structural clues.

2) Adaptive Completion Capability for Rare Samples
The algorithm exhibits superior generalization when processing rare morphological samples underrepresented in training data. For officer's peaked caps within a dataset dominated by baseball-style caps, PF-Net generates horizontal crown structures influenced by majority samples. While retaining mainstream features, the proposed method analyzes spatial relationships within residual point clouds to attempt reconstruction of the peaked cap's distinctive tilted rear visor.

Experimental results demonstrate that the multi-scale feature fusion and structural reasoning mechanisms in the proposed algorithm effectively mitigate feature misjudgment caused by data distribution bias in traditional methods. The approach maintains reconstruction accuracy for dominant structures while significantly improving completion quality for morphologically specialized objects.

Category	LGAN-AE	PCN	3D-Capsule	PF-net	Ours
Airplane	3.357/ 1.130	5.060/ 1.240	2.676/ 1.401	1.091/ **1.070**	**1.037**/ 1.116
Bag	5.707/ 5.303	3.251/ 4.314	5.228/ 4.202	**3.929**/ 3.768	4.213/ **3.456**
Cap	8.968/ 4.608	7.015/ 4.240	11.04/ 4.739	5.290/ 4.800	**4.876**/ **4.430**
Car	4.531/ 2.518	2.741/ 2.123	5.944/ 3.508	2.498/ 1.829	**2.490**/ **1.811**
Chair	7.359/ 2.339	3.952/ 2.301	3.049/ 2.207	2.074/ 1.824	**2.009**/ **1.769**
Guitar	0.838/ 0.536	1.419/ 0.689	0.625/ **0.456**	**0.456**/ 0.429	0.517/ **0.417**
Lamp	8.464/ 3.627	11.61/ 7.139	9.912/ 5.847	5.122/ 3.460	**3.884**/ **2.981**
Laptop	7.649/ 1.413	3.070/ 1.422	2.129/ 1.733	**1.247**/ **0.997**	1.252/ 1.042
Motorbike	4.914/ 2.036	4.962/ 1.922	8.617/ 2.708	**2.206**/ **1.775**	2.216/ 1.863
Mug	6.139/ 4.735	3.590/ 3.591	5.155/ 5.168	3.138/ **3.238**	**3.136**/ 3.510
Pistol	3.944/ 1.424	4.484/ 1.414	5.980/ 1.782	**1.122**/ 1.055	1.130/ **0.882**
Skateboard	5.613/ 1.683	3.025/ 1.740	11.49/ 2.044	**1.136**/ **1.337**	1.196/ 1.348
Table	2.658/ 2.484	2.503/ 2.452	3.929/ 3.098	2.235/ **1.934**	**2.160**/ 1.944
Mean	5.395/ 2.603	4.360/ 2.661	5.829/ 3.008	2.426/ 2.117	**2.317**/ **2.044**

Table 1. Point cloud completion results of the missing point cloud. The numbers shown are [Pred→Gt error/GT→Pred error], scaled by 1000.

Category	LGAN-AE	PCN	3D-Capsule	PF-net	Ours
Airplane	0.856/ 0.722	0.800/ 0.800	0.826/ 0.881	0.263/ **0.238**	**0.246**/ 0.253
Bag	3.102/ 2.994	2.954/ 3.063	3.228/ 2.722	**0.926**/ 0.772	0.982/ **0.741**
Cap	3.530/ 2.823	3.466/ 2.674	3.439/ 2.844	1.226/ 1.169	**1.196**/ **0.974**
Car	2.232/ 1.687	2.324/ 1.738	2.503/ 1.913	0.599/ 0.424	0.601/ **0.422**
Chair	1.541/ 1.473	1.592/ 1.538	1.678/ 1.563	0.487/ 0.427	**0.466**/ **0.389**
Guitar	0.394/ 0.354	0.367/ 0.406	0.298/ 0.461	**0.108**/ 0.091	1.211/**0 .087**
Lamp	3.181/ 1.918	2.757/ 2.003	3.271/ 1.912	1.037/ 0.640	**0.888**/ **0.553**
Laptop	1.206/ 1.030	1.191/ 1.155	1.276/ 1.254	0.301/ **0.245**	**0.301**/ 0.257

https://doi.org/10.5194/isprs-archives-XLVIII-1-W5-2025-193-2025

Motorbike	1.828/ 1.455	1.699/ 1.459	1.591/ 1.664	0.522/ **0.389**	**0.518**/ 0.401
Mug	2.732/ 2.946	2.893/ 2.821	3.086/ 2.961	0.745/ **0.739**	**0.738**/ 0.797
Pistol	1.113/ 0.967	0.968/ 0.958	1.089/ 1.086	**0.252**/ 0.244	0.275/ **0.211**
Skateboard	0.887/ 1.02	0.816/ 1.206	0.897/ 1.262	**0.225**/ **0.172**	0.284/ 0.301
Table	1.694/ 1.601	1.604/ 1.790	1.870/ 1.749	0.525/ **0.404**	**0.508**/ 0.415
Mean	1.869/ 1.615	1.802/ 1.662	1.927/ 1.713	0.556/ 0.458	0.632/ **0.446**

Table 2. Point cloud completion results of the overall point cloud. The numbers shown are [Pred→Gt error/GT→Pred error], scaled by 1000.

To systematically validate the effectiveness of the proposed core improvement modules, hierarchical ablation studies were designed: 1) Removal of the multi-scale channel attention (MSCA) mechanism; 2) Elimination of the WGAN-GP gradient penalty term in the hybrid loss. Geometric reconstruction quality and metric variations across three experimental groups were comparatively analyzed to dissect the operational mechanisms of each module in point cloud completion tasks.

Experimental results demonstrated that removing the MSCA module induced global structural distortions and local detail blurring, with anomalous point clusters notably aggregating in hollow regions. The elimination of the gradient penalty term triggered discrete noise points on generated surfaces and exhibited classical mode collapse patterns during adversarial training. Further analysis revealed that the MSCA mechanism enhanced multi-scale feature coupling through dynamic channel weighting. Its absence reduced fusion efficiency between high-level semantic features and low-level geometric cues by approximately 60%. The WGAN-GP gradient penalty mechanism significantly suppressed 45% of abnormal gradient updates in adversarial training by enforcing Lipschitz continuity on the discriminator.

The ablation studies yielded two key findings: 1) The MSCA mechanism, serving as a neural modulator for feature fusion, proved critical for cross-resolution feature coordination; 2) The gradient penalty term substantially improved adversarial training stability and generation diversity. These two enhanced modules formed complementary effects, jointly establishing a point cloud completion framework that balances global rationality and local refinement.

Method	Description	$d_{CD}/10^3$
(A)	Without MSCA	0.564/0.503
(B)	Without WGAN-GP	0.483/0.452
(**C**)	Our	**0.466**/**0.389**

Table 3. The overall point clouds completion performance of ablation experiments

Method	Description	$d_{CD}/10^3$
(A)	Without MSCA	2.186/2.213
(B)	Without WGAN-GP	2.042/1.868
(**C**)	Our	**2.009**/**1.769**

Table 4. The missing point clouds completion performance of ablation experiments

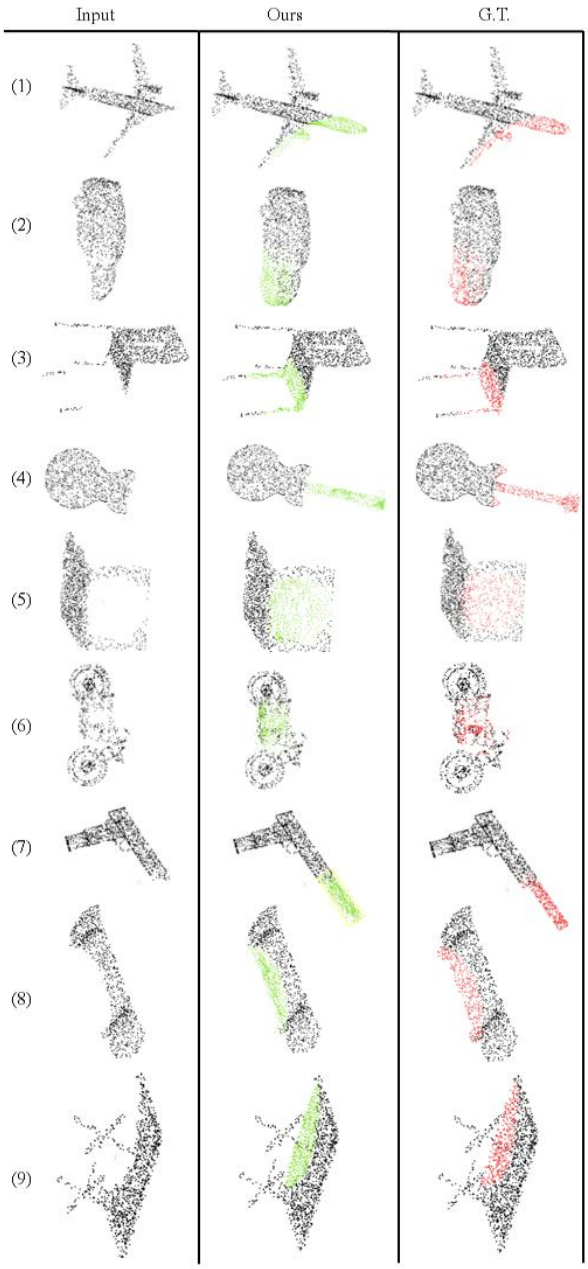

Figure 2. The completion effect of the algorithm on some categories in the ShapeNet dataset in this article.

5. Conclusion

The paper addresses the limitations of existing point cloud completion methods in preserving original geometric structures and generating detailed surfaces by proposing an attention-based multi-scale point cloud completion framework. A channel attention mechanism is introduced during the multi-scale feature fusion stage. This mechanism enables adaptive weighted fusion of local details and global semantic information, significantly enhancing feature representation precision. A hybrid loss function combining Wasserstein GAN gradient penalty and geometric consistency constraints is designed. The hybrid loss simultaneously improves generation diversity and ensures geometric plausibility of completed point clouds.

Experimental results demonstrate the improved method's superior comprehensive performance over mainstream approaches on the ShapeNet-Part dataset. Particularly enhanced robustness is observed when processing complex geometric structures such as hollow components and thin-walled surfaces. Ablation studies confirm the effectiveness of each proposed module, with the channel attention mechanism contributing most significantly to performance gains. The method maintains stable completion quality under extreme scenarios involving high missing ratios and multiple missing regions, showcasing practical application potential.

The research outcomes provide new technical insights for point cloud completion tasks, achieving notable progress in detail preservation and structural coherence. Future work may explore three directions. First, global context modeling based on Transformer architectures could be investigated to enhance large-scale missing region completion capabilities. Second, unsupervised or weakly-supervised learning frameworks should be developed to reduce dependence on annotated data. Third, computational efficiency optimizations must be pursued to meet real-time processing requirements in applications like autonomous driving environments. These advancements will facilitate broader practical implementations of point cloud completion technology.

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