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Research on Motorcycle Point Cloud Completion Method Based on GAN

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SUMMARY: *This paper presents a point cloud completion algorithm using GAN to reconstruct missing data in motorcycle point clouds. By addressing viewpoint constraints, occlusion, and sensor noise, the research tackles 3D reconstruction issues effectively. A point cloud is a collection of points that form the surface of a 3D object. It is usually created by a LiDAR or depth camera. However, data obtained is often incomplete, which creates serious difficulties in restoring shapes. The GAN framework of the proposed algorithm has a perceptual encoder; a multi-stage decoder; a downsampling module; and a supervised learning module that ensure accurate completion from global structure to local detail. The perceptual encoder utilizes a tree structure and an attention mechanism to extract features with multiple dimensions. The multi-stage decoder restores the point cloud resolution progressively and the downsampling module achieves precise point correspondence matching. Test results on the ShapeNet and MVP datasets of the authored algorithm using Chamfer Distance (CD) and Unidirectional Hausdorff Distance (UHD) shows that it outperforms PointNet and Point Completion Network (PCN) for motorcycle point cloud completion, producing point clouds with reasonable structures and clear details. In addition, the point cloud completion of physical motorcycles experiment shows that the proposed method also performs good when sparsely occluded and generates models with sharp edges and uniform structures. This work proposes two novel mechanisms, multi-stage decoding and dynamic matching, for point cloud completion.*

KEYWORDS: *deep learning; point cloud compression; feature extraction; downsampling; motorcycle*

1 Introduction

As deep learning technology has evolved rapidly, various deep learning-based point cloud completion algorithms have won great interest in the fields of computer vision and 3D shape processing. In reverse engineering a motorcycle, clay models at different stages are references. Details adjustment and development cycle time can be shortened considerably with the aid of 3D Scanning technology to digitally reconstruct clay models for able editing, modification and optimization on computer. Sensors like LiDAR and depth cameras generally capture these sculpted clay models[1,2], giving rise to an unordered point cloud that represents the motorcycle surface and the enclosing scene space. The point cloud data is sparse, disordered, and high dimensional by nature[3,4]. Owing to this, real-world applications face severe data loss and incompleteness issues due to limited viewpoints, occlusions, and sensor noise[5]. The analysis, modeling, and editing of motorcycle point clouds are severely hampered by such incompleteness. It has become a serious technical challenge. Thus, to effectively

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complete the missing motorcycle point cloud data.

One of the major challenges in point cloud completion is extracting effective features from incomplete point clouds, creating high-quality completed results, and maintaining the geometries and details of these structures. To deal with the aforementioned issues, several deep learning models and algorithms have been developed in recent years to perform point cloud completion accurately and efficiently[6,7].

The early work in point cloud completion was largely voxel-based. These voxel methods required massive shape priors, did not generalize well, and could not tackle complex situations. In 2017, Qi et al. [8]proposed a PointNet framework that allows features to be directly extracted from raw point clouds which opens a new research direction for point cloud completion[9,10]. Point cloud completion increasingly uses deep learning techniques after the success of PointNet. As the research in point cloud completion progressed, PointNet++[11], PU-Net[12], and PCN[13] were proposed with various architectures and features to improve completion performance.

In recent times, point cloud completion task has become achievable with a recent set of methodologies employing GANs[14,15]. GANs offer great adaptability and generation quality, facilitating realistic point cloud data generation through adversarial training between generator and discriminator[16]. Techniques using GAN for point cloud completion exhibit fundamental advantages and performance. improving the accuracy of completion further and the robustness of the network remains a problem in current research.

This paper proposes a point cloud completion algorithm based on GANs to overcome above problems. The algorithm employs a multi-level feature extraction module, a multi-stage decoder and a downsampling mechanism to extract features from the incomplete point clouds that progressively generate realistic completion results. The algorithm is tested on several open-sourced datasets and physical models while compared with the current mainstream point cloud completion methods to prove its efficacy. The experimental results show that the suggested algorithm outperforms other algorithms in achieving accurate and detailed completion, and has good performance and usage value.

2 Overall Algorithm Framework

As shown in Figure 1, the structure of the proposed GAN-based deep learning point cloud completion algorithm.

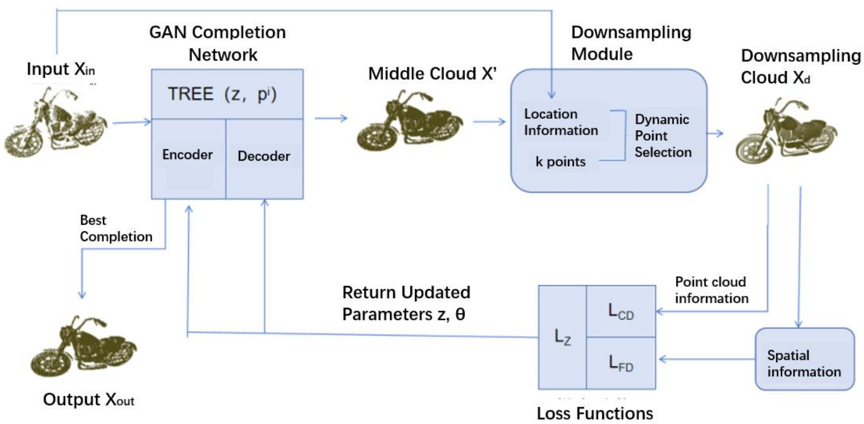

Figure 1: Framework of the Point Cloud Completion

The framework network view incorporates the GAN-based completion network, downsampling and a supervised learning module. The classifier parameters are adjusted to obtain the desired performance using comparison samples generated from downsampled point clouds. Due to the simultaneous calculation of point cloud data and position data, the completion network is able to focus on completing not only the global shape but also preserving the local details. The next sections explain how each module works and how they are designed.

2.1 Perceptual Encoder

The perceptual encoder aims to extract and fuse features from the point cloud data and obtain a fused feature vector to perform completion. The encoder as Figure 2 uses a tree structure and performs graph convolution operations on this structure due to the sparse and disorderly nature of point clouds. The encoder efficiently acquires the spatial features necessary for adapting to the disorder of point cloud data through a tree structure.

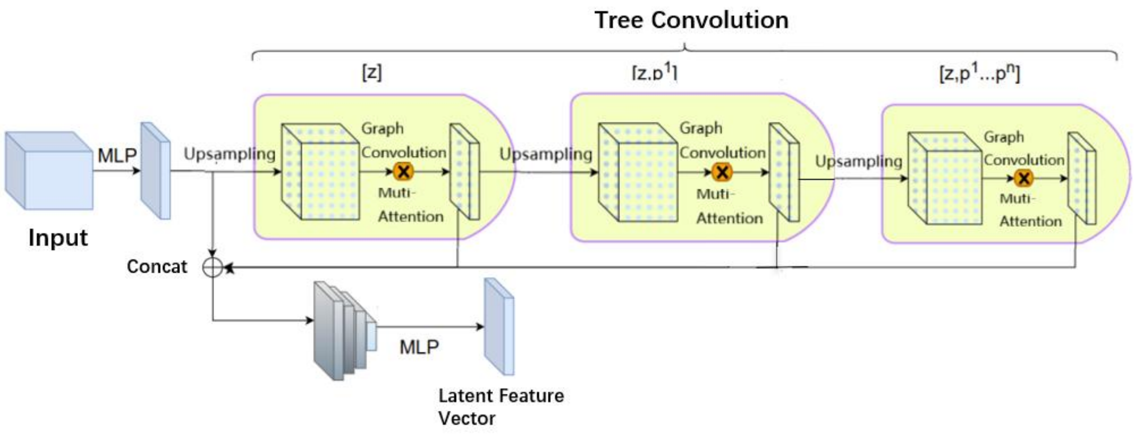

Figure 2: Perceptual Encoder

In order to improve the feature extraction, the proposed work uses a hybrid attention mechanism which contains the channel attention and the spatial attention which is used in the perceptual encoder before the graph convolution. The encoder will be more sensitive to the channels and will help specifying which channels to enhance or activate. Moreover, the spatial attention mechanism will help the model focus on the local spatial distribution of point clouds. The combination of the hybrid attention mechanism and the final output of the MLP undergoes max-pooling to produce multi-dimensional feature vectors that correctly represent the spatial distribution characteristics of the point cloud model[17,18].

$$\text{vector}(p_i) = \frac{1}{k} \sum_{p_j \in N_k(p_i)} (p_j - p_i) \tag{1}$$

Moreover, the perceptual encoder utilizes the k-nearest neighbors algorithm to calculate the direction and spatial distribution information of local neighborhood vectors for local information extraction refinement. The perceptual encoder carries out tree structure expansion in stages. As such, it continuously enhances spatial features on multiple branches and layers until it meets a predetermined completion requirement. Similarly, it provides the high-quality feature input for completion operations.

2.2 Multi-stage Decoder

The multi-stage decoder's main job is to produce complete point clouds at different resolutions while reconstructing the missing parts of the point cloud layer-wise. The decoder as Figure 3 employs a feature generation scheme that operates over multiple stages, where the feature at each stage generates a point cloud of a specific resolution. The reconstructed geometry achieves global structural consistency and local detail integrity via this process.

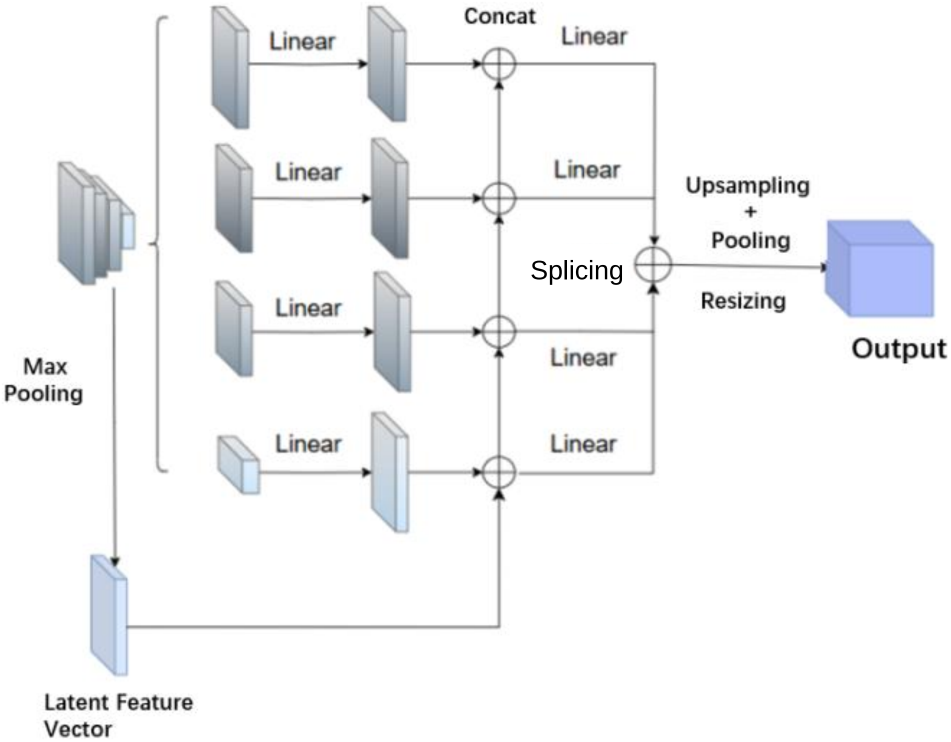

Figure 3: Multi-stage Decoder

In practice, the multi-stage decoder lowers the feature vector dimension to produce point clouds progressively that satisfy completion criteria. The decoder generates a point cloud vector through fully connected layers layer by layer. Each stage generates a point cloud feature vector. This feature vector is then concatenated with the results from the previous stage. This ensures that the new point cloud parts are structurally and qualitatively consistent. This hierarchical way of generating things makes sure that the big picture shape is correct and the little details are rich. The end product point cloud is globally complete and locally realistic.

A multi-stage completion loss function is used for training the decoder. The loss function gradually leads the generation network in completing the point cloud, ensuring that the generated point cloud at every stage remains true to the target.

2.3 Downsampling Module

The downsampling module is mainly used to downsample generated completed point clouds, which obtains samples for comparison with the input point clouds, accurately. The downsampling module builds correspondences between points dynamically so that the downsampled point clouds are consistent with the input point clouds at corresponding regions which can therefore compute completion accuracy correctly.

The downsampling module utilizes the k-Mask method, which can dynamically obtain the point correspondences between the input point cloud X_{in} and the generated point cloud X_d according to Euclidean locality. The module calculates the k-nearest neighbors N_k set for each point p_i in the input point cloud. The last output point cloud X_{out} is the collective outcome of metric nearest points obtained as a result of neighborhood relationship computations.

$$X_{\text{out}} = \bigcup_{i=1}^{\text{n}} \{ q_j \in N_k^{X_c}(p_i) \mid p_i \in X_{in} \} \tag{2}$$

In addition, in order to avoid the overfitting caused by the limited data, the downsampling module uses a weighted approach to mix the downsampled point clouds and the input point clouds to achieve coarse-to-fine conversion. This step improves the authenticity of the resultant point clouds and reduces errors, which further optimizes the model.

2.4 Supervised Learning

This paper proposes a hybrid loss function L_M to optimize performance during algorithm training. It uses were based on the distance and structural loss. This pair of measures assesses the similarity between different point clouds, ensuring that the generated point cloud has the same shape and structure as the target. This is coupled with a feature matching step, while the next measure also improves semantic consistency by adjusting the deformation of the geometric shape in the point cloud observation space.

$$L_M(X_{\text{p}}, X_{\text{in}}) = \phi L_{CD} + L_{FD} \tag{3}$$

$$L_{CD}(X_{\text{p}}, X_{\text{in}}) = \frac{1}{|X_{\text{p}}|} \sum_{p \in X_{\text{p}}} \min_{q \in X_{\text{in}}} \| p - q \|_2^2 + \frac{1}{|X_{\text{in}}|} \sum_{q \in X_{\text{in}}} \min_{p \in X_{\text{p}}} \| p - q \|_2^2 \tag{4}$$

$$L_{FD}(X_{\text{p}}, X_{\text{in}}) = \| D(X_{\text{p}}) - D(X_{\text{in}}) \|_1 \tag{5}$$

From the above equation, φ is the weight ratio, L_{CD} is the structural loss for point clouds of different sizes, and L_{FD} is the feature matching loss in the point cloud observation space, which adjusts the geometric shape more semantically. When the total loss is smaller, that shows improved network completion performance. The presented method, which uses L_{CD} and L_{FD} collectively as the loss function, achieves good performance by preventing the loss of local features while ensuring the global structural accuracy of the generated point cloud. As a result, with continuous optimization of the loss function, the network iteratively adjusts the parameters, improving the accuracy and realism of the completed point clouds.

By using the four modules together, the proposed point cloud completion algorithm can generate point clouds with good global structure and good local detail. This gives good technical support for motorcycle point cloud reconstruction.

3 Experiments and Analysis

3.1 Completion Experiments

In order to verify the effectiveness and superiority of the proposed GAN-based motorcycle point cloud completion algorithm, completion experiments on motorcycle datasets are performed. The experiments consist of two parts. The first is based on open-source datasets and is designed to compare the performance of several existing point cloud completion algorithms. The second is based on physical motorcycle models and is intended to measure the actual algorithm's completion performance. In this paper, we make use of two readily available large-scale open-source datasets, RAVDESS-emotion and AVEC-2018, along with a comparison against a few mainstream algorithms like PointNet, PCN, and PF-Net. The Completion Quality evaluation metrics chosen in this paper include Chamfer Distance (CD) and Unidirectional Hausdorff Distance (UHD).

3.1.1 Experimental environment.

The hardware and software environment of the training of this experiment are given in Table 1. The Adam gradient descent optimizer has been used with an initial learning rate of 0.001, weight decay of 0.0001, a batch size of 16, and 200 iterations in total. Batch Normalization (BN) as well as ReLU activation functions are used in the multi-scale fusion encoder and local discriminator, while only the ReLU activation function is used in the pyramid decoder structure.

Table 1: Experimental hardware and software environments

Hardware/Software	Model/Version
operating system	Windows 10
CPU	AMD Ryzen 7 5800H
GPU	NVIDIA GeForce RTX 3060
programming language	Python 3.7
framework	Pytorch1.13.1
internal storage	16GB

3.1.2 Training process

To allow a better observability of the model’s optimization, the loss variation during the training of this network is illustrated in Figure 4. New measurements are taken on the x-axis every 1000 iterations (in units of k). The y-axis is the average total loss as it runs in these 1000 iterations. The training shows the overall Chamfer Distance (CD) loss between the generated point cloud and the real point cloud reduces with the increasing step. It begins to converge at about 60000 iterations, and eventually stabilizes.

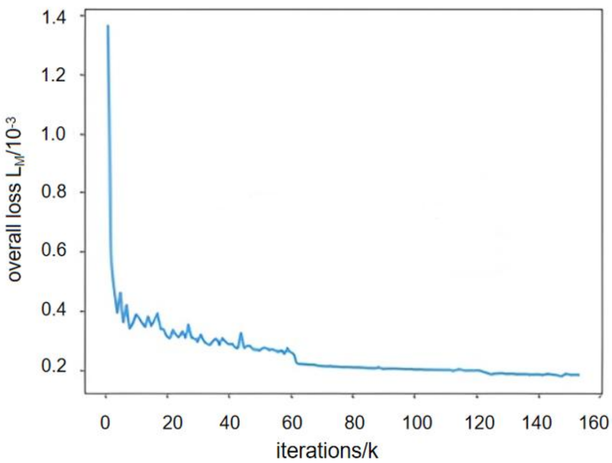

Figure 4: Loss change curve of total loss during training

3.2 Completion Experiments Based on Open-source Datasets

To show the effect of the proposed point cloud completion algorithm and to show the superiority of the proposed algorithm, completion experiments are designed using open-source datasets to compare the performance of multiple existing point cloud completion algorithms. The popular open-source datasets ShapeNet and MVP are utilized to analyze the completion effects of various algorithms on motorcycle models in 3D.

3.2.1 Open-source Datasets

The ShapeNet dataset contains a wide range of 3D model datasets for different objects. This information, which includes rich geometric and semantic information, is frequently employed for 3D shape analysis and reconstruction. In this study, 100 models from the motorcycle category from the ShapeNet dataset are selected and 2048 points are randomly removed from each model to simulate sparse and incomplete point cloud input.

The MVP dataset deals with 3D reconstruction using multiple views from different viewpoints and point cloud processing. It is an object point cloud captured from multiple views. The MVP dataset has various objects and scenes; thus, it offers a large set of test samples. In this article, we also select 100 motorcycle category models from the MVP dataset, and we perform completion testing using multi-view missing point clouds.

3.2.2 Experiments and Analysis

The missing point clouds for all models in the experiment are processed and inputted into the proposed algorithm for completion. For a complete performance assessment, we choose Chamfer Distance (CD) and Unidirectional Hausdorff Distance (UHD) as evaluation measures for completion accuracy.

Chamfer Distance measures the average distance between two point cloud models. This measure can reflect the similarity of the spatial distribution of the completed point cloud and the original complete model. A decreased completion distance (CD) demonstrates that the resultant point cloud is increasingly proximate to the target model, thus a superior completion effect. The CD formula is.

$$CD = \frac{\sum_{x \in S_1} \min_{y \in S_2} \| x - y \|_2^2}{|S_1|} + \frac{\sum_{x \in S_2} \min_{y \in S_1} \| y - x \|_2^2}{|S_2|} \tag{6}$$

S1 and S2 are two point cloud models and x and y the 3D coordinates of sampling points the point cloud models respectively. The average distance between the closest sampling points in S1 and S2 is measured by CD.

Hausdorff Distance is a distance metric which is taken to measure the distance difference which is maximum between the completed point cloud and the original incomplete point cloud. Essentially it can be taken as a detail consistency metric for the completed point cloud. Smaller UHD means that the constructed point cloud has higher fidelity. The UHD formula is.

$$UHD = \sup_{x \in S_1} \inf_{x \in S_2} \| x - y \|_2 \tag{7}$$

According to experimental results, the proposed algorithm outperforms PointNet, PCN, and PF-Net methods in the motorcycle point cloud completion task from the ShapeNet and MVP datasets. CD and UHD results of different models on the two datasets can be found in tables 2 and 3. The algorithm proposed has achieved greater accuracy for both global shape and local detail. The completed point cloud makes complete structures with smaller errors.

Table 2: Comparison of Point Cloud Completion Results of Different Models on the ShapeNet Dataset

	PointNet	PCN	PF-Net	**Ours**
CD(*10^{-3})	1.87	1.52	2.22	**1.12**

Table 3: Comparison of Point Cloud Completion Results of Different Models on the MVP Dataset

	PointNet	PCN	PF-Net	**Ours**
UHD(*10^{-2})	8.83	6.62	6.93	**5.84**

Table data reveal motorcycle point cloud completion accuracy of the proposed algorithm that is almost 100%. Results show that performance in global consistency and local details improved compared to baseline methods. The MVP dataset results show that our algorithm outperforms state-of-the-art methods with strong adaptability to generate realistic completed point clouds.

3.3 Completion Experiments Based on Physical Objects

To further verify the algorithm's performance in real scenarios, completion experiments based on physical motorcycle models are done. In the above experiments selection of a motorcycle clay model in an indoor scene has been done followed by collection of initial point cloud data using a 3D scanner. Incomplete point clouds are generated as input through structural downsampling and occlusion simulation on data.

3.3.1 Experimental Design

The experimental object was the motorcycle clay model. The structure of the motorcycle clay model was complicated with more details. The initial point cloud was sparse with occlusion. As shown in Figure 5, the algorithm's completion effect under scenarios of sparsity and incompleteness originating from real spaces is tested using scanned point cloud data.

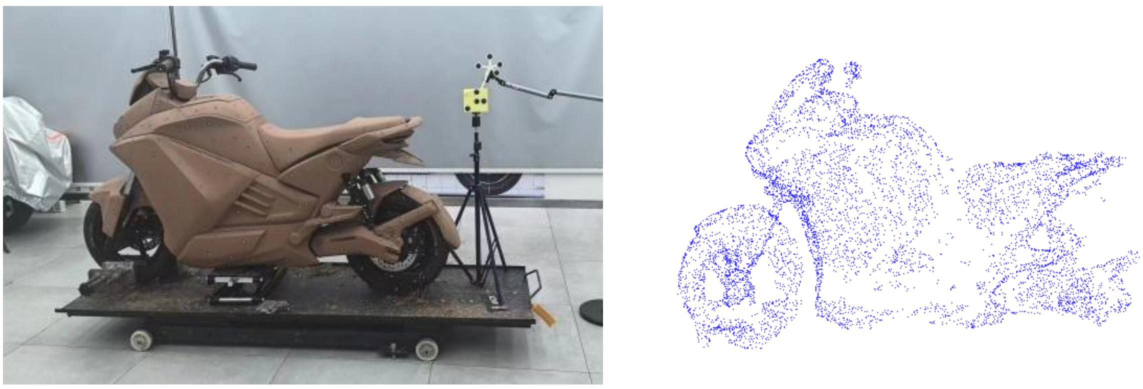

Figure 5: RGB Image and Input Image of the Motorcycle Clay Model

The Evaluation Method is based on the visual examination for integrity and edge sharpness of the finished point cloud in the physical model experiments. At the same time, to check their applicability and robustness in real scenarios, the completed point clouds generated by the proposed algorithm are visually compared with those of baseline algorithms.

3.3.2 Experimental Results

The experimental results show that the proposed point cloud completion algorithm performs very well in reconstructing the physical motorcycle point cloud. The below figure 6 shows the completion results of different algorithms on the motorcycle clay model. The point cloud model formed by the proposed method has better-defined edges with more uniform structure and full details. On the other hand, the baseline method (PointNet or PCN) performs poorly on the sparse point cloud and thus generates the completed models which have relatively blurred edges and miss details.

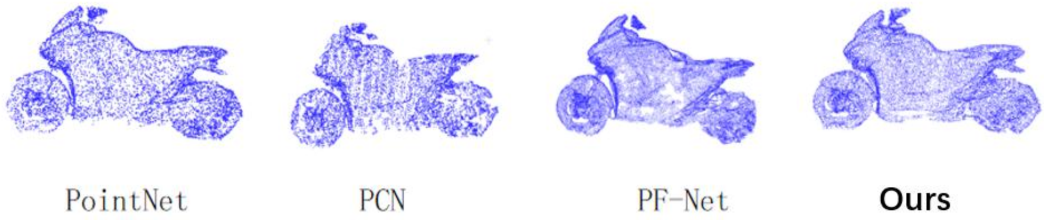

Figure 6: Point Cloud Completion Images of Various Networks

The proposed method improves edge and detail restoration of a motorcycle clay model qualitatively. The constructed point clouds are more realistic and continuous and possess good restoration capabilities in complex geometric structures. The proposed algorithm is efficient on synthetic data and is very robust on real-data completion tasks, as shown by this result.

3.4 Ablation experiment

The network in the paper is able to outperform existing methods for multimodal point cloud completion. We conducted three ablation experiments on the motorcycle class of ShapeNet dataset to prove the effectiveness of the model design. We analyzed the influence that the hybrid attention perception encoder, the multi-stage feature generator decoder, and the k-Mask downsampling module had on the network model. The completion outcomes were assessed using the CD index. To make sure we are fair in our results, all the experiments happen in the same experiment settings.

We construct different model variants A, B and C of the network model defined in this paper as part of the experiment. These are used for completion tasks on ShapeNet dataset to test the performance of the proposed model. In model A, the mixed attention module is omitted. As shown in model B, the Transformer module substitutes the multi-stage feature generation decoder to allow global feature generation directly. Model C has the downsampling module removed, making use of model D variable adjustments using the database data.

Table 4: Ablation studies on the ShapeNet dataset

	Model A	Model B	Model C	**Ours**
CD($*10^{-3}$)	1.61	2.83	2.22	1.12

The results are summarized in the table 4. Based on the comparison of model A and the proposed model, the removal of the hybrid attention module results in a slight decrease in completion performance. This shows that the hybrid attention module enhances feature extraction and accurately represents the spatial distribution characteristics of the point cloud model. Upon comparison of model B with the suggested framework, it can be seen that the multi-stage generation of features via stepwise reconstruction effectively strengthens the consistency at the global structure of the output as well as its local detail integrity. This leads to enhancement in completion performance. The comparison of model C with the proposed model reveals that achieving the same downsampling as the loss of point cloud information provides more accurate completion accuracy and better completion performance than downsampling of the generated rough point cloud.

4 Conclusion

This paper proposes a GAN-based point cloud completion algorithm that achieves remarkable performance in motorcycle point cloud completion tasks. This approach combines a GAN network architecture with perceptual encoding, multi-stage decoding and downsampling, and supervised learning modules for a balanced completion of global structure and local detail. The perceptual encoder utilizes a tree structure and a hybrid attention mechanism to facilitate the extraction of input point cloud features, allowing for the effective extraction of local geometric information and the overall spatial structure; the multi-stage decoder generates completed point clouds with progressively increasing resolution, ensuring that the generated point clouds preserve both global shape and high local detail integrity; the downsampling module effectively reduces error accumulation through accurate point correspondence matching and dynamic adjustment, resulting in consistent completion accuracy for point clouds of varying scales; the supervised learning module further enhances the performance of the model in complex scenarios through the combination of Chamfer Distance and structural loss as the loss function.

The proposed method is shown through experimental validation on open-source dataset ShapeNet and MVP that it outperforms PointNet, PCN, and PF-Net for the motorcycle point cloud completion task. The proposed algorithm is superior to the existing methods in terms of completion accuracy and error rates, given the evaluation metrics like Chamfer Distance (CD) and Hausdorff Distance (UHD). It has the ability to demonstrate significant benefits namely error and completion accuracy on sparse and incomplete data. Also, in experiments involving physical motorcycle models, the proposed algorithm displayed strong robustness, being capable of generating completed point clouds with distinct edges and uniform structures.

The novelty of this work is manifested in the introduction of multi-stage decoding and dynamic matching mechanisms that not only improve point cloud completion accuracy, but also enhance model adaptability and robustness, which affords new insights to point cloud-based industrial tasks, such as detection, recognition and reconstruction. However, this method has certain limitations. For instance, it may still struggle with maintaining details in the presence of very sparse point clouds and complex geometries. Future work could target more efficient feature extraction and decoding strategies, as well as more diversified usages of 3D perceptual information, to tackle an expanded range of point cloud completion application scenarios.

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Runru Jia was born in Changzhi, Shanxi. China, in 1999. She obtained a bachelor's degree from Tianjin University in China. She currently studying at the School of Mechanical Engineering, Tianjin University. Her main research direction is Stereo Vision and 3D Reconstruction.

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Her major research focuses on the Image Guided Robot Assist Brachytherapy. There are three issues relating to the research: Surgical planning algorithm &platform, Multiplex mode image compatible robot system and Needle-Tissue Interaction Investigation. Such robot system can substitute the surgeon during the radiation surgery, which can not only protect the surgeon from radiation but also conduct the surgery more accurately and effectively. She has published 70 papers, including 14 high level papers. The highest citation for single paper is 74, total citation is 235. 15 patents and 4 software copyrights were authorized

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