

Comprehensive Review of Deep Learning-Based 3D Point Clouds Completion Processing and Analysis

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Abstract—Point cloud completion is a generation and estimation issue derived from the partial point clouds, which plays a vital role in the applications in 3D computer vision. The progress of deep learning (DL) has impressively improved the capability and robustness of point cloud completion. However, the quality of completed point clouds is still needed to be further enhanced to meet the practical utilization. Therefore, this work aims to conduct a comprehensive survey on various methods, including point-based, convolution-based, graph-based, and generative model-based approaches, etc. And this survey summarizes the comparisons among these methods to provoke further research insights. Besides, this review sums up the commonly used datasets and illustrates the applications of point cloud completion. Eventually, we also discussed possible research trends in this promptly expanding field.

Index Terms—deep learning, point cloud, completion, 3D vision.

I. INTRODUCTION

WITH the popularity of 3D scanning devices, including LiDAR, laser or RGB-D scanners, and so on, point clouds have become easier to capture and currently provoked a great deal of researches in the fields of robots, autonomous driving, 3D modeling and fabrication. However, the raw point clouds directly collected by these devices are primarily sparse and partial due to the occlusions, reflections, transparency, and restriction of devices' resolution and angles. Therefore, generating the complete point clouds from partial observations is crucial to boost the downstream applications.

The effectiveness of point cloud completion lies in its distinct and crucial role in various computer vision applications. **3D reconstruction.** The generation of complete 3D scenes is the foundation and important technology for numerous computer vision tasks, including 3D map reconstruction with high-resolution in autonomous driving, 3D reconstruction in

robotics, and underground mining. For instance, point cloud completion in robot applications can help route planning and decision-making by constructing a 3D scene. Moreover, the large 3D environment reconstruction in underground mining space to accurately monitor mining safety. **3D detection.** The 3D object detection relies on complete point clouds to keep state-of-the-art (SOTA) performance. For example, cars in the distance captured by LiDAR tend to be sparse, often difficult to detect. **3D shape classification.** For 3D shape classification, the complete point clouds are ultimately needed by recovering from partial observations. The partial point cloud represents a small part of the object that is usually hard to recognize. Because point cloud completion plays an essential role in plenty of practical computer vision applications, there is an instant necessity for an extensive investigation of point cloud completion.

However, there are a few surveys on the completion of point cloud and downstream tasks, while the latest progress of deep learning in point cloud completion is urgently needed to be reviewed [1]–[3]. To stimulate the development of point cloud completion in industry and academy, we conducted a comprehensive review by summing up the rapid growth of point cloud completion technology in recent years (2017-2021), mainly including current deep-learning methods. Furthermore, we give comparisons among various deep-learning techniques.

Over the past several years, researchers have tried numerous methods to address this issue in deep learning. Early attempts on point cloud completion [5]–[10] tried to transfer mature methods from 2D completion tasks to 3D point clouds through voxel localization and 3D convolution. However, these methods suffer from high computational costs with increasing spatial resolution. With the tremendous success of PointNet and PointNet++ [11], [12], direct processing of 3D coordinates has become the mainstream of point cloud-based 3D analysis. This technique is further applied in many pioneering works of point cloud completion [13]–[18], in which an encoder-decoder scheme is designed to produce complete point clouds. In recent years, many other methods, such as point-based, convolution-based, folding-based, graph-based, generative model-based, and transformer-based methods, have been springing up and achieved significant results (Fig. 1).

Contrasted with the existing papers, the main contributions of the survey could be concluded as follows:

- As far as we know, it is the first survey systematically covering nearly all DL methods on point cloud comple-

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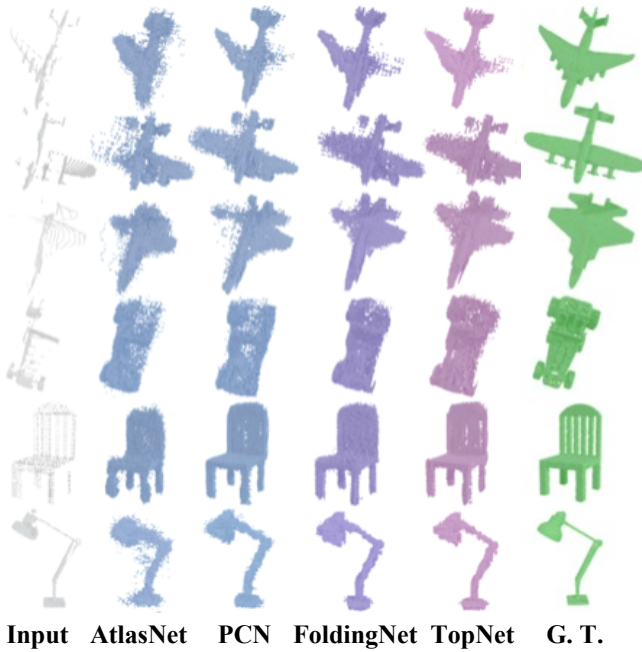


Fig. 1. Schematic diagram of completion results of commonly used point cloud algorithms [4].

tion.

- This review introduces the latest and advanced progress in point cloud completion, together with their methods and contributions.
- Systematic comparisons of existing DL methods on a few public datasets, along with compact conclusions and profound discussions, are provided.
- We will discuss future research on DL-based point cloud completion at the end of this survey to stimulate improvement in this field.

II. REASON FOR MISSING POINTS

During data acquisition, the 3D laser scanner will be affected by the characteristics of the measured object, the measurement method, and the environment, inevitably leading to the loss of point cloud (Fig. 2). For instance, the stability of the 3D scanner in the scanning process also has a particular influence on the scanning point cloud. Foot support materials, mechanical structure, and the continuous rotation of the scanner inevitably cause mechanical shake, which influences the echo and deviation between the location of the collection point cloud and the actual object to be measured. Fig. 3 summarizes the reasons for the missing point cloud.

When the data collection is completed, the point cloud also needs to carry out a series of processing, such as point cloud denoising, smoothing, registration, and fusion. At the same time, these operations will significantly exacerbate the absence of point clouds. This will not only affect the data integrity and lead to topology errors but also affect the quality of the point cloud refactoring, the 3D model reconstruction, local spatial information extraction, and subsequent processing.

III. CHALLENGES

A. Structural information challenges

The reconstruction of a complete point cloud is challenging because the structural information required for the completion task runs counter to the disordered and unstructured nature of the point cloud. 3D object point clouds in the real world could be regarded as a set of low-level and high-level configurations, including surfaces, semantic parts, geometrical elements, and so on. The 3D object point clouds have many different representations, considered a collection of point groups. Existing point cloud generation frameworks either exclude structure in their devised solutions or assume and execute a particular structure/topology for generating the complete point clouds of 3D objects, for example, a set of surfaces or manifolds. Hence, learning the structural features of the point cloud becomes critical for a better complete point cloud.

B. Fine-grained complete shapes challenges

3D shape completion is supposed to reconstruct a reasonable fine-grained complete point cloud using relational structure information that existing methods cannot capture, such as geometrical symmetry, regular arrangements, and surface smoothness. Although several works have been fully exploiting the structure information through iterative refinement [19], integration of global features and local features [20], skip-connections [21], residual connections [22], etc., more effects should be paid on the generation of the fine-grained complete shapes.

Therefore, this review will investigate the SOTA completion's performance and discuss the solutions they used in tackling these two significant challenges.

IV. DATASETS

As for 3D shape completion, the datasets could be categorized into two types: artificial datasets and real-world datasets (Table I). The most studied four datasets are as follows:

ShapeNet [23]: The Computer-Aided Design (CAD) dataset derived from PCN [18], totally containing 30974 3D models from 8 specific categories. The ground truth point clouds consist of 16384 uniformly sampled on the surfaces.

KITTI [25]: The dataset is collected through a Velodyne laser scanner. The odometry dataset was originally designed to evaluate the performance of stereo matching, which consists of LiDAR point clouds, stereo sequences, and ground truth poses. It contains 22 stereo sequences, among which the training set consists of 11 sequences (id 00-10) with ground-truth trajectories, while the evaluation set contains 11 sequences (id 11-21) without ground truth.

ModelNet40 [26]: A comprehensive set of 3D CAD models. Its objects consist of 40 categories and 13356 models.

Completion3D [17]: An online platform for evaluating shape-completion methods on the basis of a subset derived from the ShapeNet dataset. Unlike the PCN dataset, the resolution of both input and ground truth point clouds is 2048 points.

In addition to the above datasets, the Shapenet 34/55 [24] and MVP datasets [27] have recently been proposed to increase

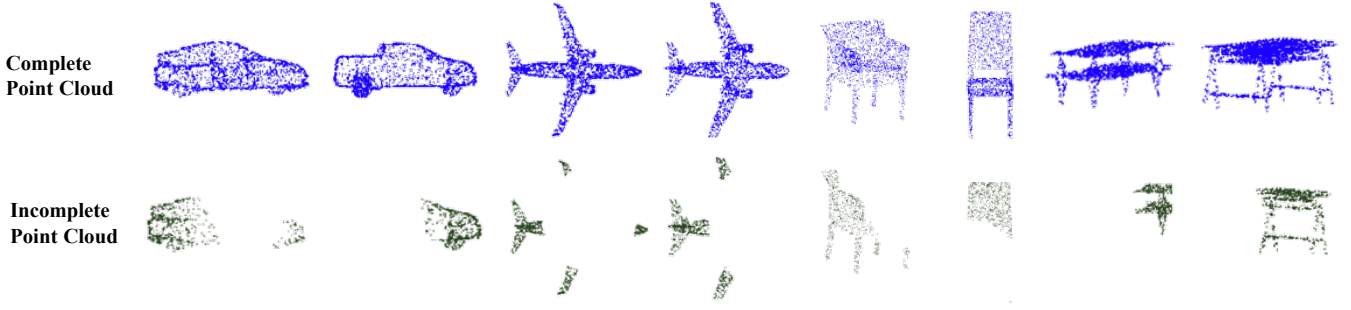


Fig. 2. Schematic of complete point cloud and missing 70% point cloud.

TABLE I
SUMMARY OF EXISTING DATASETS FOR POINT CLOUD COMPLETION.

Name	Year	Classes	Sensors or origin	Type	Views	Description
ShapeNet [23]	2015	8	CAD	Synthetic	8	Derived from ShapeNet.
ShapeNet55 [24]	2021	55	CAD	Synthetic	all possible views	Contains all the objects in ShapeNet from 55 categories.
ShapeNet34 [24]	2021	34	CAD	Synthetic	all possible views	Contains 21 unseen categories and 34 seen categories.
KITTI [25]	2012	8	RGB & LiDAR	Urban (Driving)	-	Derived from KITTI, real-world LiDAR scans. Sparse in nature.
ModelNet [26]	2015	10 or 40	CAD	Synthetic	12	Proposed by princeton.
Completion3D [17]	2019	8	CAD	Synthetic	-	Derived from ShapeNet. The partial 3D shapes are generated by back-projected 2.5D depth images from partial views into 3D space.
Multi-View Partial Point Cloud (MVP) [27]	2021	16	CAD	Synthetic	26	Diversity of uniform views; Large-scale and high-quality; Rich categories.
Single-View Point Cloud Completion [27]	2021	16	CAD	Synthetic	1	A large subset of MVP

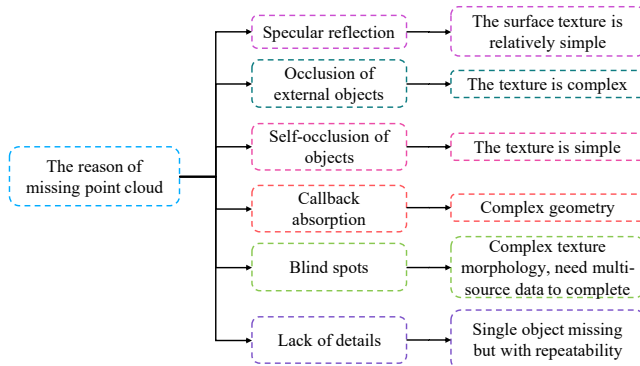


Fig. 3. Reason for missing point cloud.

the variety and number of objects, diverse viewpoints, and varying degrees of defects as close as possible to real-world objects.

V. METRICS

For 3D point cloud completion, the Chamfer Distance (CD) [28] and Earth Mover's Distance (EMD) [28] are the most frequently used performance criteria. CD tries to find the minimum distance between two sets of points, while EMD solves an optimization problem.

(1) Chamfer distance (CD)

$$CD(\mathbf{S}_1, \mathbf{S}_2) = \frac{1}{|\mathbf{S}_1|} \sum_{x \in \mathbf{S}_1} \min_{y \in \mathbf{S}_2} \|x - y\|_2 + \frac{1}{|\mathbf{S}_2|} \sum_{y \in \mathbf{S}_2} \min_{x \in \mathbf{S}_1} \|y - x\|_2 \quad (1)$$

CD represents the average distance of closest point between the output \mathbf{S}_1 and the complete point clouds \mathbf{S}_2 .

(2) Earth Mover's Distance (EMD)

EMD aims to find out a bijection $\phi: \mathbf{S}_1 \rightarrow \mathbf{S}_2$ to minimize the average distance between corresponding points from partial and complete ones. Different from CD, the size of \mathbf{S}_1 and \mathbf{S}_2 needs to be same.

$$EMD(\mathbf{S}_1, \mathbf{S}_2) = \min_{\phi: \mathbf{S}_1 \rightarrow \mathbf{S}_2} \frac{1}{|\mathbf{S}_1|} \sum_{x \in \mathbf{S}_1} \|x - \phi(x)\|_2 \quad (2)$$

(3) Fidelity error (FD), Maximum Mean Discrepancy (MMD) and consistency

Fidelity error (FD), Consistency, and minimal matching distance (MMD) are proposed by PCN as evaluation metrics [18]. Fidelity is utilized to measure how well the input is preserved, which calculates the average distance between the point in the input and the corresponding nearest neighbor in the output. MMD is used to measure how much the model's outputs reconstruct a typical car. Consistency aims to estimate how consistent the model's outputs are against variations in the inputs.

(4) Density-aware Chamfer Distance (DCD)

DCD [29] is derived from CD and it can detect disparity of density distributions.

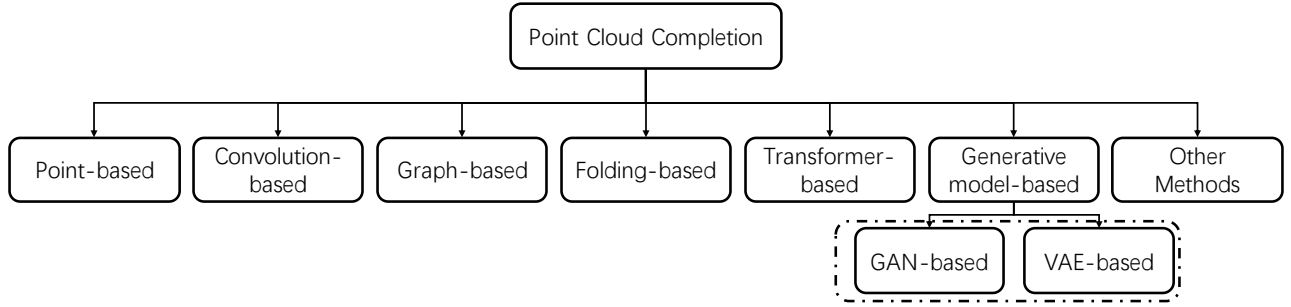


Fig. 4. Taxonomy of point cloud completion

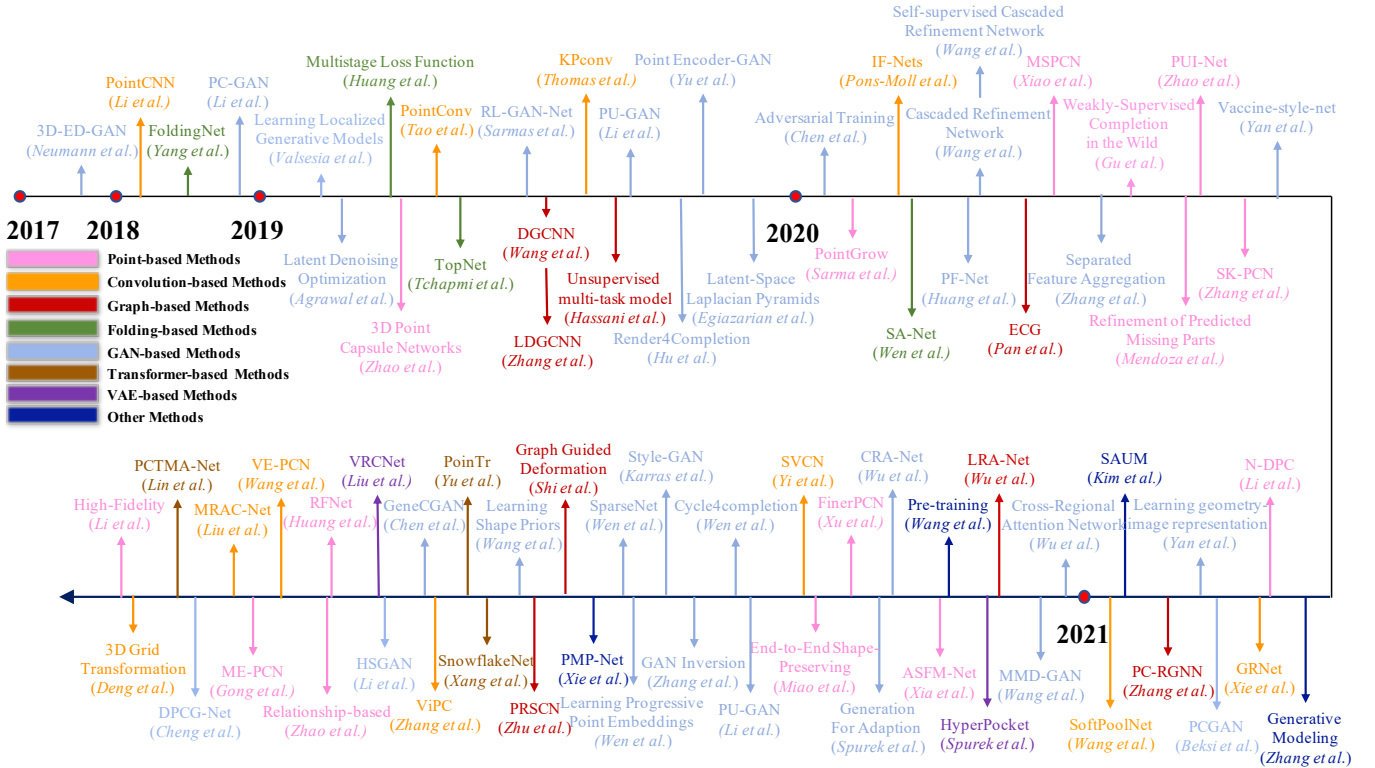


Fig. 5. Chronological summarisation of the recent and most relevant DL-based methods for point cloud completion.

$$\text{DCD}(\mathbf{S}_1, \mathbf{S}_2) = \frac{1}{2} \left(\frac{1}{|\mathbf{S}_1|} \sum_{x \in \mathbf{S}_1} \left(1 - \frac{1}{n_y} e^{-\alpha \|x - \hat{y}\|_2} + \frac{1}{|\mathbf{S}_2|} \sum_{y \in \mathbf{S}_2} \left(1 - \frac{1}{n_x} e^{-\alpha \|\hat{x} - y\|_2} \right) \right) \right) \quad (3)$$

VI. METHODS

Based on the network structure employed in point cloud completion and generation, the existing architectures could be categorized into point-based, graph-based, convolution-based, generative model-based and transformer-based methods. Nearly all milestone contributions are clearly illustrated in Fig. 4 and Fig. 5. Since most works are hybrid methods, we categorize them according to their stated highlights.

A. Point-based methods

These point-based approaches usually model every point independently by utilizing Multi-layer Perceptrons (MLPs).

The global feature is then aggregated through a symmetric function (such as Max-Pooling) because of the transformation invariance of the point clouds. Whereas the geometric information and correlations in the whole point group are still not entirely considered. As a commonly used method for processing the features, we only review the methods mainly using point-based networks in this section.

Preliminary works Pioneered by PointNet [11], a few works used MLP for the processing and recovering of the point clouds due to its concise and non-negligible ability of representations. PointNet++ [12] and TopNet [17] incorporated a hierarchical structure to take the geometric architecture into consideration. PointNet++ proposed two set abstraction layers, which intelligently aggregate multi-level information, while TopNet proposed a new decoder that generates a structured point cloud without supposing any particular structure or topology. Inspired by PointNet and PointNet++, Yu et al. [30]

proposed PU-Net learn multi-scale features by feature scaling based on sub-pixel convolutional layers (reshape). The scaling restoration method performs convolution with 1×1 kernels on extracted features. Then, the extended features are decomposed and reconstructed into a cluster of up-sampling points. And the joint loss function is utilized to evenly distribute the generated point cloud on the potential surface. Nevertheless, PU-Net is primarily designed to generate a single denser point cloud from sparse point clustering rather than do point cloud completion. It cannot fill large holes and missing parts, nor can it add meaningful points to heavily down-sampled parts of the point cloud.

To mitigate the structure loss brought by MLP, the proposed AtlasNet [13], and MSN [22] reconstruct the complete output through evaluating a set of parametric surface elements, from which the complete point clouds could be generated. Specifically, AtlasNet [13] took an additional input of a 2D point in the unit square and applied it to produce a single point on the surface. Thus, the output is a continuous image of a plane. This method could be reiterated many times to reconstruct a 3D shape from a combination of numerous surface elements. MSN [22] introduced the morphing-based decoder that can morph the unit squares as a set of surface elements aggregated into the coarse point cloud.

PCN-driven methods For the first time, Hebert et al. [18] proposed a learning-based shape completion method, Point Completion Network (PCN). Unlike existing approaches, PCN straightly works on original point clouds and does not require any assumption of structural (such as symmetry) or annotation about the underlying shape (such as semantic class). It features a decoder design that allows the generation of fine-grained completions while maintaining a small number of parameters. By combined with PCN and point-wise convolution, Xu et al. [31] devised FinerPCN to generate complete and fine point clouds in a coarse-to-fine manner by taking into account local information and reducing structural blur. After that, Zhang et al. [32] proposed a skeleton-bridged point completion network (SK-PCN). The SK-PCN features a 3D skeleton that is predicted to learn global information. Following that, the surface is completed by using displacements with skeletal points. In MSPCN, Xiao et al. [33] used a tandem of up-sampling modules to reconstruct fine-grained output and supervised each stage with key sets to generate outputs with more information and beneficial intermediate for the following phase. Furthermore, they proposed a method to identify critical sets (MVCS) for supervision by combining selected points with max-pooling and volume-down-sampling points. This MVCS could take the vital features and the overall shape into consideration.

End-to-end mechanism In point-based methods, the end-to-end manner is widely used in the network architecture. In the encoder-decoder scheme (Fig. 6), the encoder in completion architecture aims at extracting both the global 3D shape features and the regional features of each point. At the same time, the decoder generates a completion point cloud and refines it. Stilla et al. [34] devised a S2UNet network to reconstruct a more uniform and fine-detailed structure from a sparse point cloud in the applications of vehicles in an end-to-

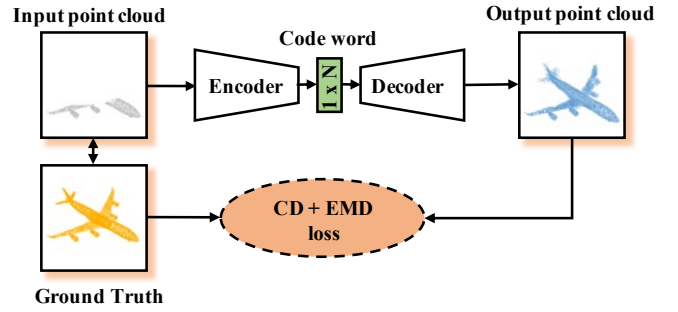


Fig. 6. The illustration of end-to-end network for point clouds completion. N represents the dimension of latent space.

end manner. Significantly, they adopt an up-sampling approach to generate a more uniform point cloud. Furthermore, they devised ASFM-Net [35], in which the asymmetrical Siamese auto-encoder (AE) generates a coarse but complete output and the following refinement unit aims to recover a final point cloud with fine-grained details. Mendoza et al. [36] proposed a network with an end-to-end pattern consisting of two neural networks: the missing part prediction network and the merging-refinement network. This method predicts and integrates missing parts while preserving the existing geometry and refining the details. Miao et al. [37] presented a shape-preserving completion network to maintain the 3D shape and recover the fine-scaled information of the reconstructed 3D shapes by designing an encoder-decoder scheme. This shape-preserving network could learn the global features and integrate regional information of adjacent points with various orientations and scales. During the decoding process, the information would be fused into latent vectors. Liao et al. [38] proposed a sparse-to-dense multi-encoder neural network (SDME-NET) in an end-to-end manner for completion while preserving details of the 3D shape. Notably, the defect point cloud would be completed and refined in two stages, from sparse to dense. In the first phase, they generated coarse but complete results based on a two-layer PointNet. In the second phase, they encoded and decoded the sparse results of the first stage using PointNet++ to yield a high-density and high-fidelity point cloud.

Moreover, two feature assemble strategies were proposed to exploit the function of multi-scale features and integrate different information to represent given parts and missing parts, respectively. The global and local feature aggregation (GLFA) and the residual feature aggregation (RFA) were dubbed [39]. These two approaches represent the two types of features and recover coordinates with the help of their combination [39]. Furthermore, a refinement module was also designed to prevent uneven distribution and outliers of the generated point cloud.

Given the scenes composed of many objects, Zhao et al. [40] devised a partial point cloud completion approach, which mainly emphasizes paired scenarios in which two objects are very close and contextually related. And a network was designed to encode the geometry of the individual shapes and the spatial relations between different objects from paired

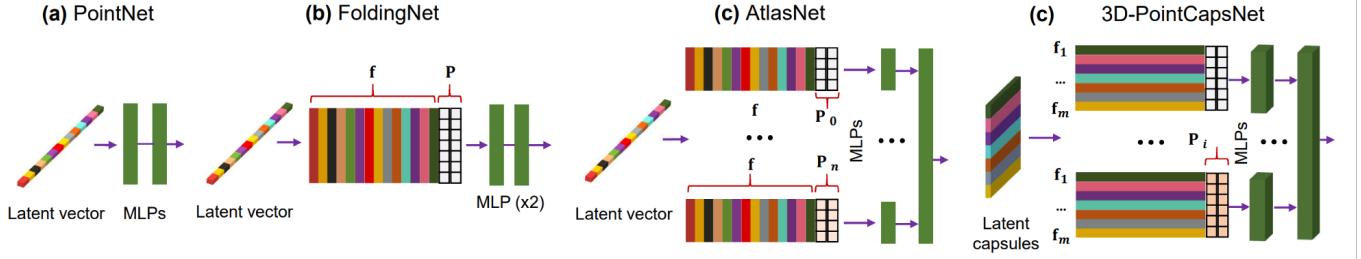


Fig. 7. Comparison of four different SOTA 3D point decoders. PointNet utilizes a single latent vector without surface assumption. FoldingNet learns a 1D latent vector together with a fixed 2D grid. The AtlasNet learns a deformation to transform multiple 2D configurations into local 2-manifolds. The point-capsule network can learn multiple latent representations, each of which can fold a distinct 2D grid onto a specific local patch.

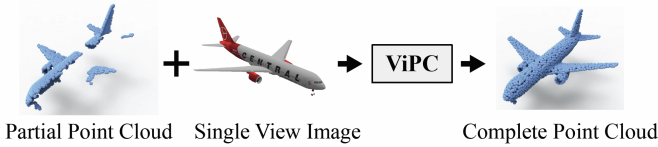


Fig. 8. ViPC is a method to complete a partial point cloud using complementary information from additional single-view images

scenes. They carried out a two-path scheme monitored by the consistency loss between different completion sequences by the merits of conditional completion. This approach could deal with the complicated case of objects severely occluding each other.

To tackle the challenging dense 3D point cloud completion problem, Li et al. [41] proposed a framework to perform end-to-end low-resolution recovery first, followed by a patch-wise noise aware upsampling. This method achieves a high-fidelity dense point cloud completion through decoding a complete but sparse shape, iterative refinement, preserving trustworthy information by symmetrization, and patch-wise up-sampling. Recently, a Recurrent Forward Network (RFNet) consisting of three modules was devised by Huang et al. [42], where there are Recurrent Feature Extraction (RFE) module, Forward Dense Completion (FDC) module, and Raw Shape Protection (RSP) module. The RFE extracts multiple global features from the incomplete point clouds for different recurrent levels, while the FDC produces the output in a coarse-to-fine pipeline. Further, the RSP introduces details from the original incomplete shapes to refine the completion results. In addition, a Sampling Chamfer Distance was proposed to capture better the shapes of models and a new Balanced Expansion Constraint to limit the expansion distances from coarse to fine.

Attention-assited methods Attention is a flexible mechanism for learning information self-adaptively, and the accumulated important information is weighted highly. By maintaining the spatial arrangements of the partial point clouds, the 3D point-capsule network [43] was devised to handle the sparse 3D point clouds with an auto-encoder. The creation of 3D capsule network results from the unified, universal 3D auto-encoders. As shown in Fig. 7, the capsule network chooses a promising direction, where a large number of convolution filters realize the learning of the capsule set through dynamic

routing. Be integrated with an encoder-decoder architecture, and the PUI-Net [44] has the advantage of extracting features with several cascaded Attention Conv Units and concatenating multi-level features before expansion. By using the extracted discriminative features, the dense feature map of the fine-grained point cloud is generated by a non-regional feature expansion unit. Li et al. [45] presented a dense point cloud completion model (N-DPC), combining self-attention units with the fusion of local features and global features. Sun et al. [46] proposed an auto-regressive network PointGrow with self-attention, which operates recurrently, with each point sampled according to a conditional distribution given its previously-generated points, allowing inter-point correlations to be well-exploited.

View-assisted methods By the merits of the modality of the images, the key challenge to solve the completion of the point cloud is to effectively integrate the features brought by pose and regional details derived from the incomplete and the global shape information from the single-view images (Fig. 8). As a sensor fusion network, Zhang et al. [47] proposed ViPC, which is a view-guided architecture. The ViPC retrieves the missing global shape information from an additional single-view image. The main contribution of ViPC lies in "Dynamic Offset Predictor," which could refine the coarse output. A multi-view consistent inference was proposed by Zwicker et al. [48] to strengthen geometric consistency in view-based 3D shape completion. And a multi-view consistency loss algorithm for inference optimization was defined, which could be implemented without ground truth supervision. Besides, the depth scan is utilized in ME-PCN [49] to make networks sensitive to shape boundaries, which enables ME-PCN to recover enriched surface details while keeping consistent local topology. In order to estimate the 6-DoF pose of 3D canonical shape with the help of several partial observations derived from the same object, Gu et al. [50] proposed a weakly-supervised approach to solve this issue. In the training process, the network uses multi-view geometric constraints to jointly optimize the canonical shapes and poses, which can deduce the complete results under the condition of a single partial input.

However, there are some limitations of point-based models.

- The point-based network mainly tackles the permutation issue. Although the point-based methods treat points independently at the local level to maintain permutation

invariance, this independence overlooks the geometric relations between the points and their neighbors. It has a fundamental limitation, leading to the loss of local features.

- Most point-based methods work in a coarse-to-fine manner. They are struggling to reconstruct object details, mainly due to two reasons: 1) the coarse outputs created from global embeddings lose the high-frequency information for 3D shapes; 2) the second stage acts as a point up-sampling function that fails to synthesize complex topologies.
- The point-based model deals directly with the points and has an extensive computation, which is inferior to the voxel-based method in large scenarios.

B. Convolution-based methods

Encouraged by the great success of convolutional neural networks (CNNs) on 2D images, several works try to utilize 3D CNNs to learn the volume representation of three-dimensional point clouds. Nevertheless, transforming a point cloud into 3D volume will bring a quantization effect: (1) Loss of details; (2) Insufficient to represent fine-grained information. Therefore, as far as we know, some works directly apply CNN on irregular, partial, and defect point clouds for 3D shape completion.

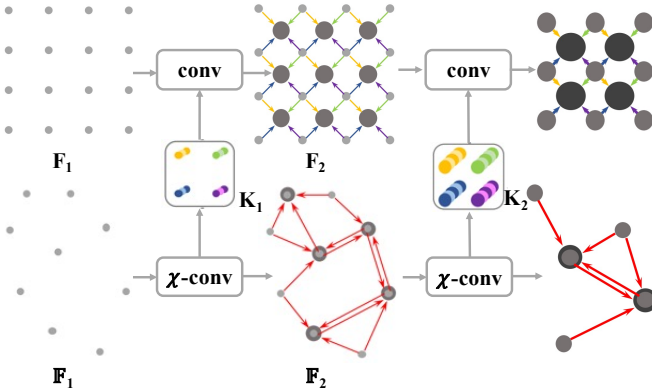


Fig. 9. The illustration of hierarchical convolution on regular grids (top) and point clouds (bottom). In regular grids, convolutions are recursively performed on local grid patches, which typically reduces the grid resolution ($4 \times 4 \rightarrow 3 \times 3 \rightarrow 2 \times 2$), while increasing the number of channels. In point cloud, \mathcal{X} -Conv is recursively applied to project or aggregate information from neighborhoods into fewer representative points but with richer information. ($9 \rightarrow 5 \rightarrow 2$).

Preliminary works In terms of the processing of point clouds, several contributions developed CNNs acting on discrete 3D grids of point cloud transformation. Hua et al. [51] defined convolution kernels on regular 3D grids, where the points are given the same weights when falling into the same grid. PointCNN [52] implements permutation invariance through a \mathcal{X} -conv transformation. And through a \mathcal{X} -conv transformation, PointCNN [52] implemented permutation invariance. In addition to CNN on discrete spaces, several methods define convolution kernels on continuous space (Fig. 9). A rigid and deformable kernel convolution (KPCConv) module was devised by Thomas et al. [53] to utilize a collection of learnable kernel points for 3D point clouds. The dynamic filter

was extended into a convolution operator dubbed PointConv by Tao et al. [54]. This operator could be employed to fulfill the deep convolution architecture.

Convolutional encoder In this field, the point cloud will first be voxelized as input of 3D CNNs. Implicit Feature Networks (IF-Nets) was devised by Pons-Moll et al. [55] to process topologies, provide consecutive and yield complete 3D shapes. IF-Nets preserves great information of extracted implicit functions, but crucially, they can also maintain details in the input and can recover articulated humans. Funkhouser et al. [56] devised Sparse Voxel Completion Network (SVCN), which is composed of two U-Net-like sub-net for structure generation and structure refinement, respectively. The structure generation sub-net convert the input data into a set of sparse voxels by voxelizing and output denser voxels that represents the 3D surfaces. Then redundant voxels are deleted from the structure refinement network.

However, the voxelization process leads to an irreversible loss of geometric information. Xie et al. [57] introduced a Gridding Residual Network (GRNet) and took the 3D grids as intermediate representations to adjust irregular point clouds. In GRNet, Gridding and Gridding Reverse methods were designed to transform point clouds into 3D grids without any loss of structural information, which 3D CNN could use. And the Cubic Feature Sampling layer was presented to extract information of adjacent points and preserve context knowledge. GRNet enables the convolutions on 3D point clouds while preserving their structural and context information. However, the voxel representation of GRNet is only used to reconstruct low-resolution shapes. Therefore, Wang et al. [58] develop VE-PCN to transform the unordered point sets into grid representations to support edge generation and point cloud reconstruction. Liu et al. [59] presented MRAC-Net, which includes an anisotropic convolutional encoder for extracting local and global features to enhance the model’s extraction ability of latent features.

Deconvolutional decoder Except for feature learning, convolutions can also be utilized in reconstructing the point clouds. Wang et al. [60] designed SoftPoolNet, which organizes the extracted features by PointNet called soft pool according to their activation. Regional convolutions were designed to maximize the global activation entropy for the decoding stage. To recover the details of the point clouds and retain the original plane structures, Deng et al. [61] proposed 3D Grid Transformation Network, where the weights were calculated for the reconstructed point clouds.

In conclusion, there are some limitations of this general volumetric 3D data representation and 3D convolutions:

- First, not all voxels or grid representations are helpful because they contain occupied and non-occupied parts of the scanning environments. Thus, the high demand for computer storage is unnecessary within this ineffective data representations.
- Second, the voxel or grid size is hard to set, affecting the scale of input data and may disrupt the spatial relationship between points.
- Third, computation and memory requirements grow cubically with the resolution.

C. Graph-based methods

Since both point clouds and graphs can be regarded as non-Euclidean structured data, exploring the relationship between points or local regions by taking them as the vertices of some graphs is convenient (Fig. 10). Regarding every point in the inputs as the vertices, the edges could be generated by graph-based networks based on the adjacent points. Hence, graph convolutions are naturally suitable for the processing of point clouds. These methods use the advantages of graph convolutions, usually convolving the spatial neighborhoods and generating a new graph by gathering the neighborhood information of each point. Compared to point-based methods, the graph-based approaches consider regional geometric details.

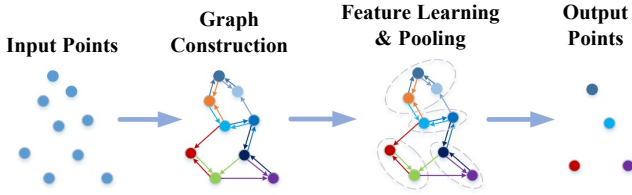


Fig. 10. An illustration of a graph-based network.

As a pioneering work, a dynamic graph convolution was introduced by DGCNN [62]. In the dynamic graph convolution, adjacent matrices could be calculated by the relations of vertexes, which come from latent space. The graph is established in the feature space and can be dynamically updated in the DGCNN. Moreover, EdgeConv was devised to calculate graphs in every network layer dynamically and could be integrated with the existing architectures (Fig. 11). In addition, LDGCNN [63] removes the transformation and connects the multi-level features learned in different layers in DGCNN. Thus, the performance and model size can be optimized. Stimulated by DGCNN, Hassani, and Haley [64] introduced the multi-level network to exploit points and shape features for self-supervised reconstruction. Furthermore, following DGCNN, DCG [65] encodes regional links as feature vectors and refines the point clouds in a coarse-to-fine manner.

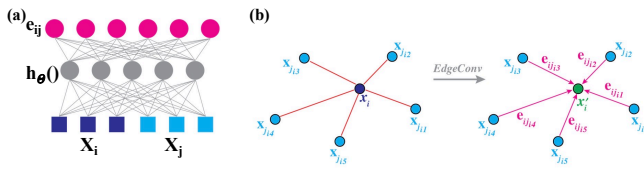


Fig. 11. (a) An edge feature e_{ij} is calculated from the pair of point x_i and x_j . (b) The EdgeConv operator. The output of EdgeConv is computed by converging the edge features of all edges emitted by each connected vertex.

Except for the dynamic graph convolution, PointNet++ [12] could also be regarded as a type of method using graph convolution to exploit information from fixed adjacencies of sampled center points. Combining with graph convolution, Pan [20] designed a hierarchical encoder to refine the local geometric details by propagating multi-scale edge features, which were captured by skeleton generation. Following that, the

Edge-aware Feature Expansion (EFE) module was proposed to expand/up-sample information of points by highlighting the regional edge of the point. Nodeshuffle and Inception DenseGCN [66] were proposed by Qian et al. The former utilizes a Graph Convolutional Network (GCN) to encode regional point features from adjacent points better, while the latter aggregate features at multiple scales. The PU-GAN is a new point up-sampling pipeline when combining the Inception DenseGCN with NodeShuffle [67]. Shen et al. [68] proposed a Graph Guided Deformation Network, in which the input data and intermediate generation were considered as controlling and supporting points, respectively, and models the optimization guided by graph convolutional network for the task of point cloud completion. This network simulates the Least Square Laplace Deformation process via mesh deformation methods, which has the adaptive ability to change the geometric details of the modeling and reduces the gap between the mesh deformation algorithm and the completion task. Li et al. [69] designed the PRSCN, which firstly uses Point Rank Sampling approaches to rank and sample points via regional outline form more objectively. Subsequently, considering the connections among features from a different level, a Cross-Cascade unit was designed to integrate features. Besides, Leap-type EdgeConv was proposed to expand the receptive field with kernel size maintained. Moreover, by utilizing global features and local features, LRA-Net [70] was proposed to recover complete point clouds with more details and smoother shapes, which are derived from the structure of PointNet and Graph Convolutional Network (GCN).

Attention-assisted GCN Furthermore, the attentional mechanism is also introduced into GCN. To recover finer shapes, Wu et al. [71] introduced a learning-based method. They sample local regions of partial inputs, encode their features, and combine them with exploited global features. After the graph is built, all the regional features are gathered, and the graph is convolved with multi-head attention. Graph attention mechanism enables each local feature vector to be searched across the regions and selectively absorb other local features based on relationships in high-dimensional feature space. CRA-Net [72] designed a cross-regional attention unit based on graph attention. This module quantifies underlying connections among regional features under specific contexts and is explained by global features. Given such links, every conditional regional feature vector can be searched as graph attention. In PC-RGNN [73], a graph neural network module was designed, which captures the relations between points comprehensively through the local-global attention mechanism and context aggregation based on a multi-scale graph, greatly enhancing the coding features.

But there are two challenges for constructing graph-based networks as follows:

- First, defining an operator that is suitable for dynamically sized neighborhoods and maintaining the weight sharing scheme of CNNs.
- Second, exploiting the spatial and geometric relationships among each node's neighbors.

D. Folding-based methods

As a generic architecture firstly proved by Yang et al. [74], a Folding-based decoder can reconstruct arbitrary point clouds from 2D grids for objects with detailed structures with low reconstruction errors (Fig. 12, Fig. 13). The FoldingNet is like applying a "virtual force" that deforms/cuts/stretches a 2D grid lattice onto a 3D surface. This deforming force should be affected or modulated by the interconnections induced by the adjacent meshes. Due to the intermediate folding steps and training processes in the decoder could be represented by reconstruction points, the gradual variation of folding force could be seen intuitively.

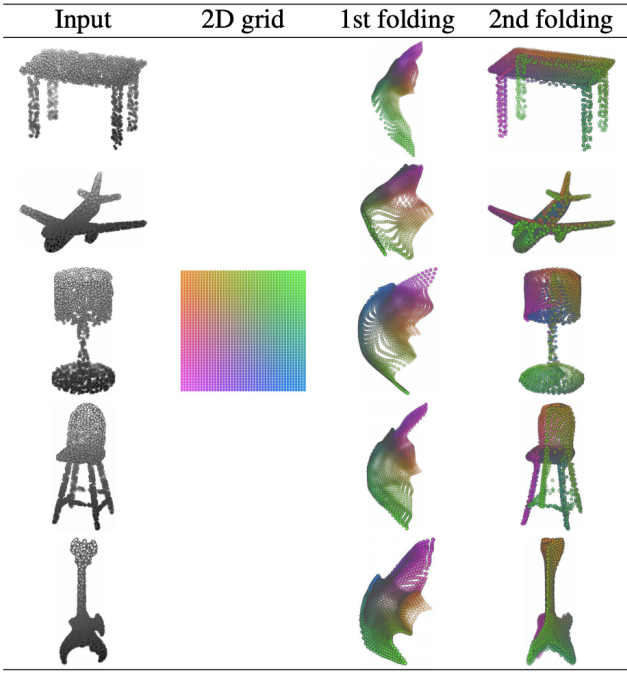


Fig. 12. Description of two-step-folding decoding. The second column shows the 2D grid to be folded when decoding. The third column consists of the results underwent one folding operation. The fourth column composes of the results after the two folding. The final result is also the recovered point cloud. The color gradient is used to explain the correspondence between the 2D grids in the second column and the recovered point clouds in the last two ones after folding [74].

Folding-based methods (KCNet [75] and MSN [76]) usually sample 2D grids from a 2D plane with fixed size and then concatenate them with the global shape representation extracted by the point cloud feature encoder. KCNet [75], AtlasNet [13], MSN [76] and SA-Net [21] reconstruct the complete object by evaluating a set of parametric surface elements and learn projections from 2D to 3D surface elements.

Besides, TopNet [17] explores the hierarchical root tree architecture as a decoder to produce a random grouping of points and visually demonstrates the architecture exploited by the decoder through visualizing a node in the tree decoder as a collection of its children.

To fully utilize structure details, Wen et al. [21] proposed Skip-Attention Network, which contributed two aspects: A skip-attention mechanism was adopted to explore the regional structure details of partial inputs, and a structure-preserving

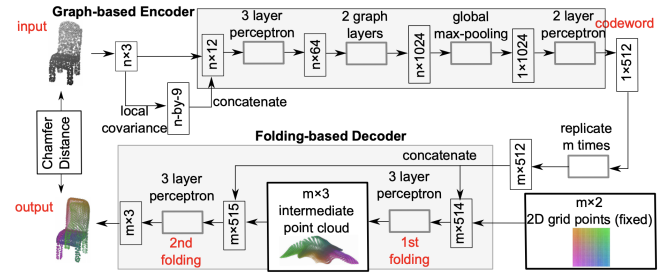


Fig. 13. The architecture of FoldingNet [74].

decoder using hierarchical folding was proposed to make use of the selected geometric information.

Despite their limited success, the great details of an object are often missed. Existing folding-based methods, such as PCN [18], FoldingNet [74] and TopNet [17], fail to produce the structure details of an object to certain extent. One of the reasons is that they only rely on a single global shape representation to predict the entire point cloud. In contrast, the rich local region information that helps recover the detailed geometry is not fully utilized. Zong et al. [4] proposed an adaptive sampling and hierarchical folding network (ASHF-Net), in which the denoising auto-encoder with an adaptive sampling module to learn local region features, while the hierarchical folding decoder with the gated skip-attention and multi-resolution completion objectives make use of local structural details. Li et al. [77] combined a Point-based encoder with an FC-based decoder and a Folding-based decoder to produce the complete output, and this model with multistage loss function can be directly applied on the completion of point clouds.

Up-to-now, FoldingNet is the most widely used decoding block in the existing point cloud completion network. There is a drawback in FoldingNet, promoting researchers to build new decoder blocks.

- The folding manipulation samples the same 2D grids for each parent point, overlooking the local shape characteristics contained in the parent points.

E. GAN-based methods

Compared to traditional CNN, the GAN [78] architecture utilizes a discriminator implicitly learning to estimate the point collections provided by the generator (Fig. 14). Due to the characteristics of 3D data, the integration of GAN in point cloud completion possesses several inherent challenges:

- Different from the grid structure of 2D images, where the locations of pixels are clearly defined. In contrast, point clouds with different 3d shapes are highly unstructured. In general, GANs trained on three-dimensional shapes produce point clouds with significant inhomogeneity. That is, points are not evenly distributed on the surface of the shape. This inhomogeneity can lead to shapes with unwanted holes, undermining the integrity of our predictions.
- The disorder of point cloud makes the completion task significantly different from two-dimensional image com-

pletion. In 2D image rendering, one can easily measure the reconstructed consistency between partial input visible region and predicted output given mesh aligned pixel corresponding. This comparison is challenging in 3D shape completion because the corresponding regions of two 3D shapes may be located at different positions in 3D space. GAN inversion results in poor reconstruction, which jeopardizes the shape-completion mission.

- Whereas simple GANs can only yield a small size of (1024 or 2048) point collections because of the complicated point distribution and the notoriously hard training of GANs.

Therefore, the researchers greatly improved the point cloud completion based on the traditional GAN.

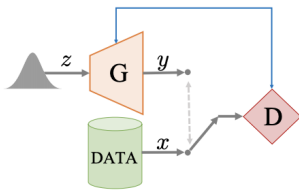


Fig. 14. An description of a generative adversarial networks. The basic architecture is on basis of antagonism between a generator (G) and a discriminator (D). The G is designed to produce points that seem different from real data ($x \sim p_{data}$) via a random sample from a simple distribution $z \sim p_z$ through the generator function. The task of the discriminator is to distinguish synthetic samples from real ones.

End-to-end mechanism End-to-end learning is commonly used in 3D point cloud completion. By the integration of a 3D Encoder-Decoder Generative Adversarial Network (3D-ED-GAN) and a Long-term Recurrent Convolutional Network (LRCN), Wang et al. [79] introduced a new structure. 3D-ED-GAN makes use of an encoder to map voxelized 3D shapes into a probabilistic latent space and uses a GAN to facilitate the decoder generate the complete volumetric shapes with the help of the latent feature representations. Nevertheless, these approaches are only able to use 3D volumes as inputs or get a voxel representation for results.

Achlioptas et al. [80] devised r-GAN with both generator and discriminator using fully connected layers. The AE was trained to learn the latent space and then trained in the generative model in this fixed latent representation. The l-GANs were trained in the latent space, which was more easily trained than simple GANs with coverage of data distributions, fulfilling better recovery. In the training of latent representation, the capability of multi-class GAN is almost the same as that of class-specific GAN. Gurumurthy et al. [81] have devised a scheme utilizing latent GAN and AE. Nevertheless, they used a time-consuming optimization procedure for every batch of inputs to choose the best seed for GAN. Achlioptas et al. [82] introduced a deep AE network with great recovery performance and generalization capacity. In the 3D recognitions, the shape transformation is realized by algebraic operation. They conducted in-depth studies on different generative models, such as GAN operated on the original inputs, GANs significantly trained in the AEs fixed latent space, together with Gaussian mixture models (GMMS).

Yu et al. [83] devised a point encoder GAN, where the max-pooling layer was utilized to tackle the irregular issue in the learning process, and two T-Nets (derived from PointNet) were added in the encoder-decoder architecture to represent the characteristics of the inputs better. And a hybrid recovery loss function was proposed to compute the diversity between two groups of disordered data. Chen et al. [84] proposed an end-to-end conditional GAN called GeneCGAN. From the heredity perspective, a simulated genetic (SG) layer was devised. It is executed in a hierarchical root tree using ancestor information and the connection of neighborhoods. Through a prior fusion strategy, the global feature is appended to the tree's root node as conditional information, and the conditional probability distribution of the inputs is learned.

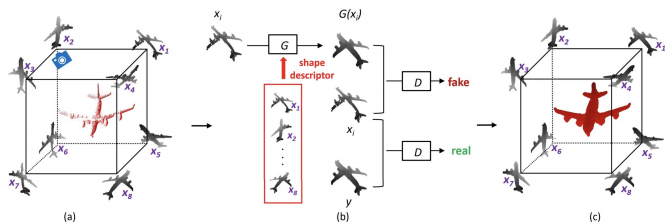


Fig. 15. An illustration of a generative multi-view representation. For example, (a) 8 depth maps of defect inputs were rendered from 8 viewpoints; (b) These introduced 8 depth maps are completed through a multi-view completion network, including adversarial losses, producing 8 completed depth maps; (c) The 8 depth maps are back-projected into a completed shape.

The effective latent space representations of the point cloud provide important and fundamental information that can be utilized for 3D shape reconstruction. Wen et al. [85] presented Cycle4Completion with two synchronous cycle transformations between the latent spaces of complete 3D shapes and incomplete 3D shapes to learn from complete ones. The cycle transformation could facilitate the model to learn about 3D shapes through studying to produce complete or incomplete shapes with the help of complementary shapes. Chen et al. [86] proposed a framework for unpaired shape completion, the core of which is an adaptation network that acts as a generator to transform latent codes of the original point scans and maps them to underlying latent spaces of clean and complete object scans. These two latent spaces regularize the issue by limiting the transfer issue to respective data manifolds. Zhang et al. [87] presented ShapeInversion to introduce GAN inversion into shape completion for the first time. ShapeInversion leverages a GAN pre-trained on complete shapes by searching for a latent code to obtain the complete shape that best reconstructs the input of a given part. In this way, ShapeInversion eliminates the need for paired training data and can combine rich prior information in a well-trained generation model. Combining the latent-space GAN and Laplacian GAN, Egiazarian et al. [88] devised a multi-level network that can produce 3D objects with increasing levels of details. Based on GAN, a PU-GAN was presented by Li et al. [67], which is an up-sampling network that aims to learn the point distributions from the latent space. This PU-GAN can also up-sample points over patches on the surfaces of the object. In the generator, an up-down-up expansion module was constructed to up-sample

point features, which has an error feedback unit and self-correction functions. Moreover, a self-attention unit was also developed to increase the integration of features.

Furthermore, Li et al. [89] proposed a two-fold modification of GAN (PC-GAN). In PC-GAN, hierarchical Bayesian networks and implicit generative architectures are combined through hierarchical and interpretable sampling. The key of this approach lies in the posterior inference model, which is trained for hidden variables. Besides, rather than using the SOTA Wasserstein GAN objective, a sandwiching objective was devised to result in a compact Wasserstein distance estimate than the typically utilized dual form. Hence, PC-GAN provided a generic architecture to comprise the existing GAN easily. Tao et al. [90] devised a dual-generators network, in which the first generator was designed to learn point embeddings, while the second one was utilized to refine the generated point cloud based on a depth-first point embedding to generate a uniform output. To minimize the influence of noises and geometrical loss of incomplete point cloud, PF-Net [91] retains the spatial arrangement of incomplete inputs and can calculate the complicated geometry of the missing area. To this end, PF-Net uses a multi-level generation based on feature points to predict the missing parts in a hierarchical network. PF-Net also utilizes multi-stage completion and adversarial loss to produce more realistic missing regions. Among them, the adversarial loss can better solve the problem of multiple modes in the prediction. Cheng et al. [92] proposed an end-to-end generative adversarial network-based dense point cloud completion architecture (DPCG-Net). The DPCG-Net designed two generative adversarial network (GAN)-based modules that translate point cloud completion into mapping between global feature distributions obtained by encoding partial point clouds and ground truth, respectively.

Refinement Besides, the refinement strategy is also commonly integrated with GAN. Wang et al. [93] developed a feature alignment approach for learning the shape prior. Moreover, a coarse-to-fine method was devised to combine the shape prior with the fine phase. The loss of feature alignment comprises an L2 distance and an adversarial loss derived from Maximum Mean Discrepancy Generative Adversarial Network (MMD-GAN). Wang et al. [94] devised a point completion network with a cascaded refinement network (CRN) as a generator to synthesize these missing parts with high quality by using the details of inputs. Moreover, they designed a patch discriminator, which uses adversarial training to know the precise point distribution and punish the generated shapes differently from the ground truth. Furthermore, to generate high-quality targets with detailed geometry, Wang et al. [19] expanded this strategy to synthesize fine-grained targets. The complex distribution of point clouds can be learned by considering local details of local inputs and adversarial training.

Multi-view GAN The views of the same 3D model share some common information that can be explored, including global and regional information as seen from various angles. Zwicker et al. [95] proposed a multi-view completion net (MVCN) (Fig. 15), which leverages information from all views of a 3D shape to assist the completion of every single view. Benefiting from the multi-view presentations and

network architecture with conditional GAN, MVCN enhances the performance of 3D completion. Liu et al. [96] tried to convert the three-dimensional point cloud generation issue to a two-dimensional geometry image generation problem and introduced a adversarial VAE to optimize the GIG proposed by combining adversarial learning with VAE. While it's easy to create depth maps of 3D shapes on their own, there are two drawbacks. First, they do not encourage consistency between depth maps from the same 3D object, which influences the accuracy of 3D objects obtained through back-projecting completed depth maps. Second, they could not complete a depth map and use information from other depth maps of the same 3D object. The accuracy of completing a single depth map is limited.

Integrated with RL More recently, reinforcement learning (RL) has been integrated into GAN. Sarmad et al. [97] presented RL-GAN-Net in which a reinforcement learning mechanism can control the GAN. The architecture can transform noisy defect input data into full shape with high fidelity through the control of GAN. Vaccine-Style-Net [98] was carried out in the function space of 3D surfaces, and the 3D surface is represented as the continuous decision boundary function. At the same time, an RL unit is embedded to derive the complete 3D geometry from the partial inputs.

Integrated with GCN Except for RL, GCN is also commonly utilized with GAN. Valsesia et al. [99], [100] studied the unsupervised problem of generating models using graph convolution. They emphasize the generator of GAN and define graph convolution methods when the graph is the generator's output without prior knowledge. They devised structure learns to produce local features to approximate the embedding of output geometry. They also investigated the issue of defining an up-sampling layer of a graph convolution to learn to sample more efficiently using self-similarity. Xie et al. [101] presented a SpareNet by utilizing EdgeConv is channel-attentive to learns the regional features and global shape and using shape features as style code to adjust the normalization layer during the process folding to enhance its capabilities. Moreover, a differentiable renderer is used to project the complete point cloud onto the depth map, and adversarial training is applied to promote the perception of reality from different viewpoints. Li et al. [102] devised a Hierarchical Self-Attention GAN (HSGAN) to use a random code and transforms it hierarchically into a representation graph by combining GCN and self-attention. In this model, the topology of the global graph is embedded into shape generation, and latent topology information is utilized to recover the geometry structure of the 3D shape.

F. Variational autoencoders (VAEs)-based methods

Classic AEs and VAEs are trained on a complete 3D object. The model's weight is then determined to generate a latent representation of incomplete data. Finally, the generative model completes partial inputs in conditional generative network settings. The completion production is based on the learning mode distribution explicitly extracted from the complete shape. There are no paired completion instances in the training dataset.

TABLE II
COMPARISON OF 3D POINT CLOUDS COMPLETION PERFORMANCES ON THE SHAPENET. HERE, 'CD' REPRESENTS THE MEAN CHAMFER DISTANCE AND 'EMD' REPRESENTS THE MEAN EARTH MOVER'S DISTANCE. THE '-' REPRESENTS THE PERFORMANCES ARE UNREACHABLE. (THE CD LOSS IS SCALED BY 1000 AND EMD LOSS IS SCALED BY 100.)

Methods		ShapeNet		
		CD (Value/Resolution)	EMD (Value/Resolution)	F-Score@1% (Value/Resolution)
Point-based Methods	N-DPC [45]	10.25/16384	6.05/16384	-
	MSN [22]	10.00/8192	3.78/8192	-
	MSPCN w/ MVCS [33]	0.94/2048	-	-
	PCN [18]	5.70/16384	4.28/16384	-
	SK-PCN [32]	0.18/2048	0.50/2048	-
	ASFM-Net [35]	12.09/4096	-	-
	FinerPCN [31]	16.65/2048	6.14/2048	-
	Refinement of Predicted Missing Parts [31]	0.34/2048	-	-
	Weakly-Supervised 3D Shape Completion [50]	26.40/8196 (3 categories)	-	-
	Multi-View Consistent Inference [48]	8.05/2048	-	-
	SDME-Net [38]	17.00/4096	4.42/4096	-
Convolution-based Methods	GRNet [57]	0.27/16384	-	0.71/16384
	ViPC [47]	3.31/2048 (ShapeNet-ViPC)	-	0.59/2048 (ShapeNet-ViPC)
	SoftPoolNet [60]	5.94/16384	4.80/1024	-
Graph-based Methods	CRA-Net [72]	24.24/2048	-	-
	ECG [20]	10.19/2048	-	-
	Graph-Guided Deformation Network [68]	0.60/2048	-	-
	PRSCN [69]	4.48/2048 (ShapeNet-part(14)) 4.78/2048 (ShapeNet-part(16))	-	-
	DCG [65]	0.33/2048	-	-
	LRA-Net [70]	2.60/2048	0.19/2048	-
Folding-based Methods	ASHF-Net [4]	0.26/16384	-	-
	TopNet [17]	0.97/2048	-	-
	SA-Net [21]	0.77/2048	-	-
	Multistage Loss Function [77]	1.86/2048	5.02/16384	-
GAN-based Methods	Graph Guided Deformation [68]	0.60/2048	-	-
	CRN [94]	2.29/2048	-	-
	Latent-Space Laplacian Pyramids [88]	0.34/2048 (3 categories)	4.16/2048 (3 categories)	-
	MMD-GAN [93] (Learning Shape Priors)	8.50/2048	-	-
	NSFA [39]	0.81/16384	-	-
	PF-Net [91]	0.56/2048	-	-
	Cascaded Refinement Network [94]	8.29/16384	-	-
	Cycle4Completion [85]	1.14/2048	-	-
	ShapeInversion [87]	1.49/2048	-	0.84/2048
	MVCN (Render4Completion) [95]	1.86/2048	-	-
	GencCGAN [84]	2.63/2048	2.70/2048	-
	SpareNet [101]	0.52/2048	0.19/2048	-
Transformer-based Methods	SnowflakeNet [103]	1.86/2048	-	-
	PoinTr [24]	1.09/8192 (ShapeNet-55)	-	0.46/8192
Other Methods	PMP-Net [104]	8.66/2048	-	-

TABLE III
COMPARISON OF 3D POINT CLOUDS COMPLETION PERFORMANCES ON THE COMPLETIONKITTI. 'MMD' REPRESENTS THE MINIMAL MATCHING DISTANCE AND 'FD' REPRESENTS THE FIDELITY DISTANCE. THE '-' STANDS FOR THE PERFORMANCES ARE UNREACHABLE.

Methods		CompletionKITTI		
		MMD (Value/Resolution)	FD (Value/Resolution)	Consistency(Value/Resolution)
Point-based Methods	PCN [18]	0.0185/16384	0.028/16384	0.01163/16384
	ASFNet [35]	-	0.014/4096	0.020/4096
Convolution-based Methods	GRNet [57]	-	-	0.313/16384
	SoftPoolNet [60]	0.01465/16384	0.02171/16384	0.00992/16384
Folding-based Methods	ASHF-Net [4]	0.541/16384	0.773/16384	0.298/16384
GAN-based Methods	MMD-GAN [93]	-	0.034/2048	-
	NSFA [39]	-	0.0261/16384	-
	SpareNet	0.368/2048	1.461/2048	0.249/2048
Transformer-based Methods	PoinTr [24]	-	0.526/8192	-

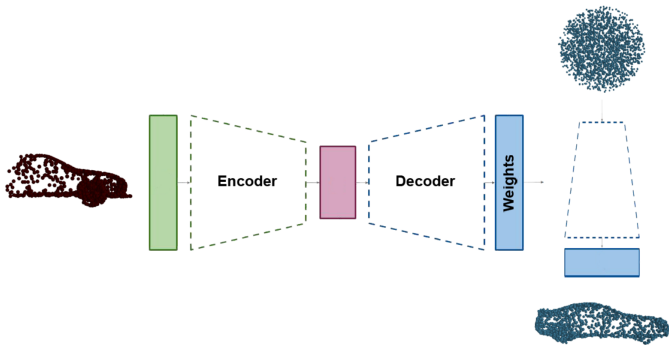


Fig. 16. HyperPocket architecture with single VAE encoder [27].

Spurek et al. [105] introduced a Variational Autoencoder architecture named HyperPocket, which is capable of disentangling latent representations and thus generating multiple variants of completed 3D point clouds (Fig. 16). The point cloud processing was split into two unconnected data streams and utilized a hyper network paradigm to fill what are known as pockets of space left by missing object parts. Liu et al. [27] devised a Variational Relational Point Completion Network (VRCNet) to leverage a dual-path unit together with a VAE-based relational enhancement module for probabilistic modeling. And multiple relational modules were devised that could efficiently utilize and integrate multilevel point information, including the Point Self-Attention Kernel and the Point Selective Kernel Unit. Zamorski et al. [106] presented an application of three generative modeling approaches and tested the architectures of AE, VAE, and Adversarial Autoencoder both quantitatively and qualitatively. Besides, they introduced a method that uses the extended PointNet model (Double PointNet) to manipulate points based on both local features and the global shape.

G. Transformer-based methods

Transformer [107] was firstly proposed for encoding sentences in natural language processing, and after that became popular in the areas of 2D computer vision (CV) [108], [109]. Pioneered by PCT [110], Pointformer [111], and PointTransformer [112], the transformer has begun its journey in point cloud process.

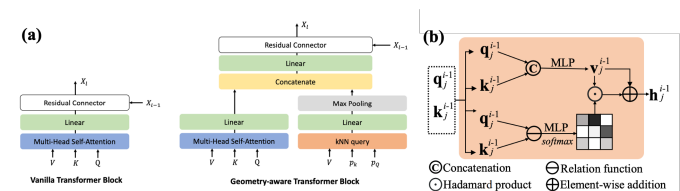


Fig. 17. (a) Compares of the transformer block and the geometry-aware transformer block [24]; (b) The detailed structure of skip-transformer [103].

By the merits of the representation learning ability of transformer, Yu et al. [24] regarded point cloud completion as a set-to-set translation issue and proposed a transformer encoder-decoder structure for point cloud completion. By representing the point cloud as a set of disordered points with position embeddings, The point cloud can be converted to a series of point proxies. The transformer was employed for the point cloud generation. To facilitate transformers to use better the inductive bias of 3D geometric structures of the point cloud, they further design a geometry-aware block that explicitly simulates local geometric relations (Fig. 17a).

Rather than utilizing the representation learning ability of transformer, Xiang et al. [103] devised SnowflakeNet with Snowflake Point Deconvolution (SPD), applying transformer-based structure to the decoding procedure. The SnowflakeNet models the generation of complete point clouds as the snowflake-like growth of points in 3D space. After each SPD, child points are gradually generated by splitting their parent points. The idea of revealing geometry details is to introduce a skip-transformer in SPD to learn point splitting modes

TABLE IV

COMPARISON OF 3D POINT CLOUDS COMPLETION PERFORMANCES ON THE MODELNET AND COMPLETION3D. 'CD' REPRESENTS THE MEAN CHAMFER DISTANCE AND 'EMD' REPRESENTS THE MEAN EARTH MOVER'S DISTANCE. THE '-' STANDS FOR THE PERFORMANCES ARE UNREACHABLE. (THE CD LOSS IS SCALED BY 1000 AND EMD LOSS IS SCALED BY 100.)

Methods		ModelNet		Completion3D	
		CD (Value/Resolution)	EMD (Value/Resolution)	CD (Value/Resolution)	EMD (Value/Resolution)
Point-based Methods	ASFM-Net [35]	-	-	18.570/2048	-
	An End-to-End Shape-Preserving [37]	-	-	26.900/1024	3.370/1024
Convolution-based Methods	GRNet [57]	-	-	1.046/2048	-
Graph-based Methods	PRSCN [69]	4.649/2048	-	-	-
	Cross-Regional Attention Network [72]	27.000/16384	11.700/16384	-	-
GAN-based Methods	CRN [94]	2.293/2048	-	-	-
	Cascaded Refinement Network [94]	2.472/16384	-	0.914/16384	-
Transformer-based Methods	SnowflakeNet [103]	-	-	0.760/16384	-
VAE-based Methods	HyperPocket [27]	-	-	1.791/2048	-
Other Methods	PMP-Net [104]	-	-	0.923/2048	-

that can best suit local regions. Skip-transformer utilizes an attention mechanism to summarize the splitting patterns used in the previous SPD layer, resulting in the splitting of the current SPD layer. The locally compact, structured point cloud produced by SPD can accurately capture the structure features of 3D shape in local patches, enabling the network to predict highly detailed geometries (Fig. 17b).

Moreover, Lin et al. [113] presented PCTMA-Net, where the Transformer's attention mechanism can extract the local context within a point cloud and exploit its incomplete local structure details. A morphing-atlas-based point generation network fully utilizes the extracted point Transformer feature to predict the missing region using charts defined on the shape.

However, there are some limitations of transformer-based models.

- Due to the amount of the transformer parameter, the model is too large to deploy on devices compared with other methods.
- Except for the visual interpretation of attention in SA-Net [21], the mechanism of transformer for enhanced performance is hard to interpret.

H. Other methods

In addition to the methods mentioned above, researchers have also carried out studies on up-sampling and pre-train methods.

Wen et al. [104] designed PMP-Net to complete the point cloud by moving every point in the incomplete input to ensure the shortest total distance of the point moving path (PMP). Therefore, PMP-Net predicts the unique PMP of each point based on the constraint of the total point movement distance. Kim et al. [114] introduced a shape completion framework to preserve both the global contexts and the local features, in which a Symmetry-Aware Up-sampling Module (SAUM) was

devised to preserve the geometric details and take advantage of the symmetry of shape completion. Kusner et al. [115] developed a pre-training mechanism named Occlusion Completion (OcCo), which works by shielding the occluded points from observations from different camera views and then optimizing the completion model. In this way, This method learns a pre-trained representation that could recognize the inherent visual constraints embedded in a real point cloud.

VII. COMPARISON

This section summarises the results of latest methods on the several datasets. This section will compare the performance of these approaches and provide some advices for future works.

A. Summary of the performance on ShapeNet, ModelNet, and Completion3D with ground truth provided.

The ShapeNet is the most commonly utilized dataset for 3D shape completion. These three datasets all belong to synthetic benchmarks. As shown in Table II, III, V, and Fig. s1, s2 (see the Supplementary Material), there are the results performed by various methods, and some inferences could be drawn as follow:

- The point-based models with MLP, integrated as the basic unit, are widely utilized to learn the point-wise information.
- The graph-based and GAN-based networks can fulfill excellent results on completing 3D point clouds. More attention needs to be paid to the combination of these two methods.
- Transformer-based models have recently attracted more attention because of their powerful ability to process irregular data. The SOTA methods could be credited to the latest SnowflakeNet. Nevertheless, extending

TABLE V
SUMMARIZING OF MILESTONE DL NETWORKS BASED ON THE POINT CLOUD PROCESSING METHODS.

Methods		Highlights	limitation
Point-based methods	AtlasNet [13]	AtlasNet regards a 3D shape as a collection of parametric surface elements and infers a surface representation.	The reconstruction largely depends on the reiterated many times.
	MSN [22]	MSN predicts a set of parametric surface elements and undergoes a combination with the partial input by a sampling algorithm.	Fail to generate fine-grained details of object shape.
	PCN [18]	Combing the fully connected network and FoldingNet, PCN performs the coarse-to-fine completion.	Incapable of synthesizing shape details.
	ASFM-Net [35]	ASFM-Net is an asymmetrical Siamese auto-encoder model to learn a shape prior information.	The visualization performance of completion can be further improved.
	SK-PCN [32]	SK-PCN predicts the 3D skeleton to acquire the global structure and completes the surface by learning skeletal points' displacements.	The meso-skeleton only focus on the overall shapes.
Convolution-based methods	GRNet [57]	GRNet introduces 3D grids as intermediate representations to regularize unordered point clouds.	It is still subject to the resolution.
	VE-PCN [58]	VE-PCN incorporates the structure information into the shape completion by leveraging edge generation..	The edges only focus on high frequency components.
	ViPC [47]	An extra single-view image explicitly provides the global structural prior information for completion.	The surface of the results is not that smooth.
Graph-based methods	PRSCN [69]	PRSCN proposes a Point Rank Sampling to select feature points and eliminate the influence of outlier points. Point Rank Sampling pays more attention to the local relative importance and generates high fidelity geometrical shapes.	It can only predict the missing parts.
	ECG [20]	ECG applies several modules with graph convolutions for edge-aware feature learning and/or preserving.	There are noises around the completion result.
	DCG [65]	DCG employs the point set auto-encoder first to produce a sparsely coarse shape and then refines it by encoding neighborhood connectivity on a graph representation.	The performance can be further enhanced.
	CRA-Net [72]	The CRA module facilitates each local feature vector to search the regions within a fully-connected graph and selectively absorbs other local features based on their relationships with graph convolution.	Insensitive to edge information.
Folding-based methods	FoldingNet [74]	A two-stage generation process is commonly used to assume that 3D objects can be recovered from a 2D-manifold.	The implicit intermediate is hard to be constrained explicitly.
	SA-Net [21]	SA-Net proposes hierarchical folding in the multi-stage points generation decoder.	It is difficult to interpret and constrain the implicit representation of the target shape from the intermediate layer to help refine the shape in the local region.
	ASHF-Net [4]	ASHF-Net proposes a hierarchical folding decoder with the gated skip-attention and multi-resolution completion target to exploit the local structure details of the incomplete inputs.	The surface of the results is not that smooth.
GAN-based methods	PF-Net [91]	PF-Net uses a feature-points-based multi-scale generating network and combines multi-stage completion loss and adversarial loss to generate realistic missing regions.	The resulting shape lacks local geometric details.
	ShapeInversion [87]	ShapeInversion addresses the domain gaps between virtual and real-world partial scans and various simulated partial shapes through GAN inversion.	Both shape completion and manipulation are conducted on a model pre-trained with a single category
	MMD-GAN (Learning Shape Priors)	MMD-GAN proposes 3D feature alignment methods to learn the shape priors from complete and partial point clouds.	Insensitive to edge information.
	NSFA [39]	NSFA proposes two separated feature aggregation namely GLFA and RFA, considers the existing known part and the missing part separately.	Suffer from the information loss of structure details.
	Cascaded Refinement Network [94]	The generator of CRN is a cascaded refinement network, exploiting the details of the partial inputs and synthesizing the missing parts with high quality.	The performance can be further enhanced.
Transformer-based methods	PoinTr [24]	PoinTr regards point cloud completion as a set-to-set translation issue and employs a transformer encoder-decoder architecture.	The model is relatively large due to transformer's large number of parameters.
	SnowflakeNet [103]	SnowflakeNet introduces a skip-transformer to learn splitting patterns in Snowflake Point Deconvolution for progressively increasing the number of points.	The resulting point cloud is not evenly distributed

transformer-based models into the spectral domain remains a challenge.

B. Summary of the performance on CompletionKITTI without ground truth provided.

Tables IV, V, and Fig. s3 (see the Supplementary Material) give the performance achieved by numerous methods on the CompletionKITTI, and from which some observations could be listed as follow:

- The CompletionKITTI dataset is derived from the real-world captured KITTI dataset. The intrinsic challenges such as no ground truth provided and ultimately sparse in some instances bring difficulties to point cloud completion.
- As shown in Table III, the Point-based, GAN-based, and Transformer-based methods all have achieved completion effects facing such challenges.
- Besides, some works [50], [87] are devised for point cloud in the real world, and more effective should be paid on these directions.

VIII. APPLICATIONS

The point cloud completion is a vital technology in many applications and has accumulated several achievements. Therefore, in this section, the applications of point cloud completion in numerous fields will be introduced.

A. Construction

Because of the enormous benefits, the completed point cloud is urgently needed by industries to enhance productivity, such as the manufacturing [116], [117], and construction industry [118], [119]. For instance, as shown in Fig. 18a, the point cloud was acquired at a precast concrete manufacturing plant. Compared with traditional measurement approaches, such as manual or other measurements based on equipment, the point cloud data captured by sensors has the merits of a higher measurement rate and higher measurement accuracy.

B. Mining space

Nowadays, 3D point cloud processing technology has been applied frequently in mining. For example, the national robotics engineering center of the United States can successfully draw a high-precision, 3D map of underground roads using the point cloud data obtained by a 3D laser scanner and then propose an intelligent mining model based on the 3D map [120]. The 3D point cloud data is used to describe and draw the whole fully-mechanized mining face, accurately and intuitively reflecting the spatial position relationship between coal wall and fully-mechanized mining equipment. This method provides directional information for the scraper conveyor to adjust the displacement of the hydraulic support in time (Fig. 18b). Besides, the complete point cloud will provide more accurate information for mining space.

C. Autonomous driving

On the one hand, the main task of autopilot is to find a compact 3D point cloud representation and maintain the capacity for reconstruction; As shown in Fig. 20. reconstruction helps to store data in autonomous driving. Because every autonomous vehicle (AV) has to store high-definition maps and collect real-time LiDAR sweeps, data storage would be expensive for a large fleet of AVs. While no mature compression standard is available to deal with large-scale open scene 3D point clouds [121], reconstruction technology can provide 3D point cloud compression and reduce the cost of data storage. Point cloud completion can be used for reconstruction to obtain a higher quality point cloud.

On the other hand, the production of high-definition maps is relatively expensive and impractical for every scene. Hence, semantic scene completion is proposed to complete the sparse LiDAR sweeps. In this area, convolution-based methods have been widely applied. However, the details of scenes are missing due to the voxelization of the point cloud [122]–[124]. To tackle this issue, the completion of sparse LiDAR sweeps through point-based methods might be a solution.

Images, point clouds, and radar data could be combined to produce precise, geo-referenced, and information-rich cues for AVs' navigation and decision-making [125]. Data from low-end LiDAR and high-end LiDAR are also fused. At the same time, there are some difficulties in merging these data. Most importantly, in the fusion of cross-source data, the sparsity of point cloud leads to inconsistent and missing data. Therefore, the point cloud completion can be utilized to tackle the sparsity of real-time LiDAR sweeps.

D. Robotics

Point cloud technology has been widely used in robotics in recent years. Localization and mapping are crucial for autonomous mobile robot navigation in unknown environments. **Localization** A accurate 6-degree of freedom (6-DoF) pose is ideal for unmanned aerial vehicles (UAVs) or humanoid robots and robots performing missions. However, localization with RGB-D cameras in a 3D environment still presents some challenges: (1) Robots often take a long time to orient themselves in a 3D environment; (2) There are changes in the 3D environment. For instance, as shown in Fig. 18d, Luo et al. presented a method to determine the 6-DoF global positioning of the robot without a given initial pose, which is dubbed the Fast Scene Recognition and Alignment (FSRA) system [126]. **Mapping** More attention has been paid to the three-dimensional environment point cloud maps in public and engineering space. 3D environment maps are helpful for autonomous mobile robots in indoor environments without GPS. However, these precise locations and mappings still require a complete point cloud as a prerequisite.

IX. FUTURE DIRECTION AND OPEN QUESTIONS

Based on the above discussions, there are two problems to be solved : (1) To achieve high precision and robust completion by overcoming the above challenges. (2) Fast operation speed and high accuracy guarantee. In this part, we propose several

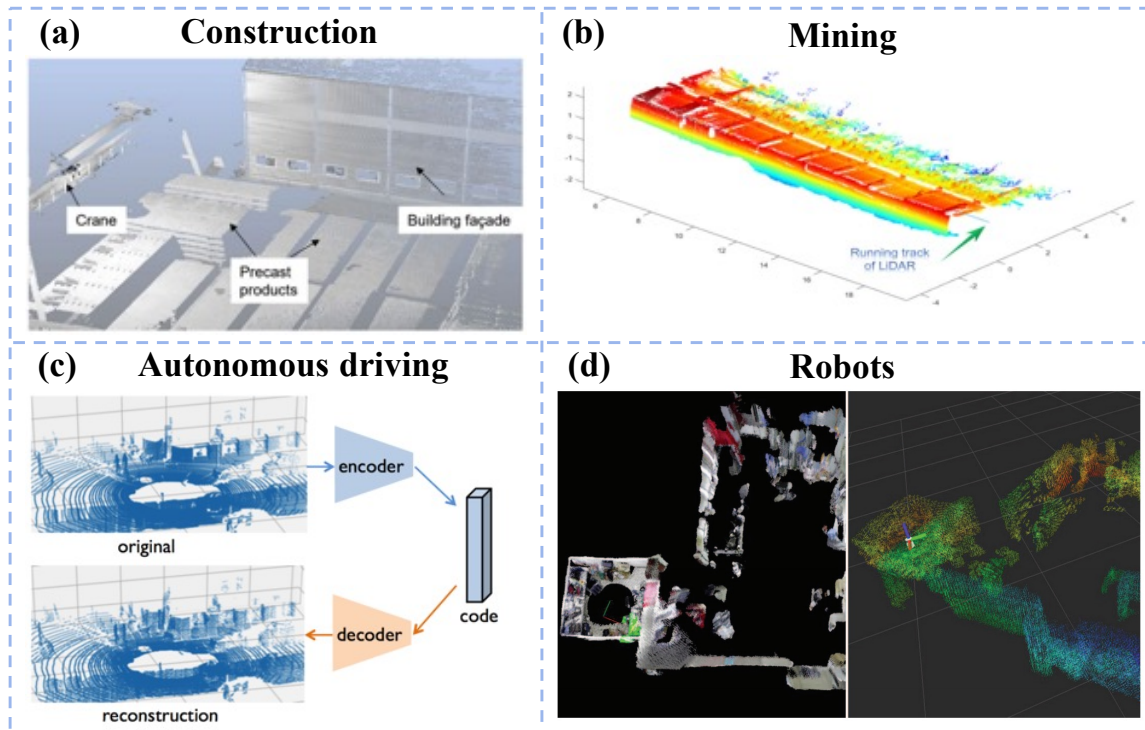


Fig. 18. Point cloud completion in (a) construction, (b) fully mechanized mining equipment, (c) 3D reconstruction, and (c) localization of autonomous indoor robots.

future research directions to enhance the performance of DL-based point cloud network as follows:

- Although the DL-based point cloud completion has achieved impressive results, almost all the existing networks are conducted in the current datasets, such as ShapeNet, ModelNet, and Completion3D. These datasets are derived from the CAD. Therefore, it is urgent to develop new datasets captured in the real world to make the networks more robust in the wild.
- Due to the disorder and irregularity of point cloud, the early processing of point cloud is mainly voxelization. Still, this processing method will lead to the loss of effective information of the point cloud and increased computational complexity. Although feature extraction networks have been designed, such as PointNet and GCN, more effects should be paid to feature learning. In the decoder design, there are only fully connected networks, FoldingNet, and the newly-proposed transformer-based decoder network. Moreover, establishing a corresponding loss function is a significant challenge to be solved in the future.
- Although there are remarkable achievements in 3-D DL models, including PointNet [11], PointNet++ [12], PointCNN [52], DGCNN [62], FoldingNet [74], PF-Net [91], PoinTr [24] and other work [104], [114], [115]. As transformer outperforms various of methods in computer vision, the transformer-based methods will be widely studied in the next few years.
- Although unsupervised methods [87], [99], [100] have been developed, more effects should be paid on it because

the captured point clouds from real-world could not obtain the ground truth.

- Limited networks can fulfill robust real-time completion tasks. In addition, the network training process is time-consuming. Research emphasis should be focused on lightweight and compact structure design.

X. CONCLUSION

This paper has carried out a systematic review of the approaches for 3D point completion. A comprehensive taxonomy and performance comparison of these approaches has been summed up. The advantages and limitations of each method are introduced, and the possible research directions are listed. This paper details DL's research challenges and opportunities in point cloud completion to promote the potential developments.

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