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Enhancing 3D Precision: Point Cloud Upsampling Methods — A Review

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Abstract
Enhancing the resolution of point clouds is crucial in achieving detailed and precise 3D representations for various applications. Factors such as sensor calibration, scanning range, and environmental capability play a pivotal role in determining the overall quality of the captured point cloud data. Moreover, issues related to noise, occlusions, and sensor limitations can further impact the accuracy of the modelling outcome, underscoring the importance of optimizing point cloud resolution. Thus, researchers started to build new architectures with the aim of produce more dense and complete representation with higher resolution. Different methods have been created to achieve successful upsampling, such as interpolation techniques, deep learning strategies, and optimization algorithms. In this paper, we take a closer look at this exceptionally fast-developing field of science. According to this aim, the reader will better understand point cloud upsampling technology.

Keywords
point cloud upsampling, deep learning, point cloud compression, surface consolidation, 3D point cloud

1 Introduction

The evolution of digital imaging technologies has not only improved the quality – especially the resolution – and accessibility of visual content, but has also expanded its applications in various fields. The resolution of digital images can be defined through four key aspects: geometric, radiometric, spectral, and temporal resolution. Geometric resolution refers to the spatial detail in an image, determined by the pixel size and density; higher geometric resolution provides finer detail and greater clarity. Radiometric resolution indicates the sensitivity of the imaging system to variations in light intensity, defined by the number of bits per pixel; higher radiometric resolution allows for more precise discrimination of subtle differences in brightness. Spectral resolution pertains to the ability of the imaging system to capture information across different wavelengths of light, enabling the differentiation of various materials based on their spectral signatures. Temporal resolution describes the frequency at which images are captured over time, which is crucial for monitoring dynamic processes; higher temporal resolution means more frequent image capture, allowing for detailed tracking of changes over time. Each of these resolution aspects plays a critical role in the effective use and analysis of digital images across various scientific and practical applications. In the following, we will focus on geometric resolution, leaving out the word "geometric" to mean resolution. Resolution is essential in the image processing workflow because it directly affects the detail and precision that can be extracted from an image. Higher resolution allows for more accurate identification and analysis of fine features, which is crucial in applications such as medical diagnostics, remote sensing, and forensic analysis. However, increasing the geometric resolution in imaging hardware presents significant challenges. Enhancing resolution requires more advanced sensors with higher pixel densities, which can be costly and complex to manufacture. Additionally, higher resolution

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images demand greater storage capacity and processing power, posing further technical and logistical hurdles. Increasing the resolution of a digital image post-capture, often called image upscaling/upsampling or super-resolution, involves sophisticated computational techniques rather than changes to the original imaging hardware. One common approach is to use interpolation methods, such as bilinear or bicubic interpolation, which estimate new pixel values based on surrounding pixels. More advanced techniques include machine learning algorithms, which can predict high-resolution details from low-resolution images by learning patterns from large datasets. These methods can produce significantly enhanced images by reconstructing finer details and textures. However, while these techniques can improve apparent geometric resolution, they are limited by the quality and quantity of the input data and the algorithm's ability to predict missing information accurately. Point cloud (PC) super-resolution has the same goal: to create high-resolution, fine-detailed, dense, and noiseless point cloud data with uniform density [1]. Thus, analyzing and interpreting 3D environments in LiDAR sensing, 3D mapping, and object recognition becomes easier.

Several definitions of point cloud have been identified in previous researches [2–7]. Point cloud data consists of geometric points, often identified as three-dimensional points with coordinates (x, y, z) in a given/chosen coordinate system. In theory, it consists of points located in space and determining the shape of an object or its distribution in 3D space. This collection of points may hold a vast amount of data. PCs are typically acquired from different sources like laser scanners (or alternatively LiDARs abbreviating Light Detection and Ranging), depth cameras, or photogrammetry methods. PC technology is essential in a variety of fields, including geosciences [8–10], 3D reconstruction and modelling [11–13] virtual reality [14–16], robotics [17–19], autonomous driving [20–22], architecture [23–25], archelogy [26–28] and agriculture [29–31], bathymetry mapping [32]. However, the accuracy of PC data may be restricted by distance, angle, overlap ratio, noise, or surface characteristics. These restrictions can lead to a lack of precise details and decrease geometric precision.

PC upsampling entails producing a more precise and elaborate depiction of the initial data points within the PC data, essential for creating 3D models and reconstructions with increased accuracy. Image super-resolution methods cannot simply solve point cloud upsampling tasks due to calculation difficulties arising from an extra dimension. Moreover, PC data usually do not have any spatial structure [33]. Thus, the term PC super-resolution is not widely used; however, some published works use this name [34–38]. Instead of super-resolution, the methods' named "point cloud upsampling" is becoming more popular in current research. In order to enhance a lower-quality input of a three-dimensional scene, advanced computational techniques, intricate algorithms, and sophisticated models are necessary to produce a more detailed and denser version of higher-quality PC data. By applying advanced algorithms and Deep Learning (DL) techniques, super-resolution methods can increase the level of detail, improve geometric accuracy, and recover missing information in low-quality PCs. This skill offers many possible applications in 3D reconstruction, object identification, scene comprehension, and augmented reality [39–43].

2 Challenges in point cloud data and the importance of point cloud upsampling

PC data presents various challenges that impact its quality, accuracy, and usability. Understanding and addressing these challenges are crucial for effectively utilizing PC technology. One of the primary challenges in PC data is low resolution [44, 45]. PCs acquired from sensors or scanners may have limited resolution due to hardware constraints or sparse sampling. This results in a lack of fine-grained details and an incomplete representation of the underlying object or scene (Fig. 1) [46, 47]. PC upsampling methods play a critical role in addressing this challenge by enhancing the resolution and level of detail in PC data [48, 49]. Non-uniform sampling patterns (Fig. 2) can also present challenges in PC data. PC data are often acquired using sensors with varying point densities, resulting in an uneven distribution of points across the scene. In some areas, the point density may be too sparse, while in others, it may be too dense. This inconsistency in point densities can affect subsequent processing tasks and lead to inaccuracies in the representation of the object's surface. Upsampling methods can effectively handle non-uniformly sampled PCs by inferring missing points and improving the overall density and consistency of the data. Additionally, the computational complexity associated with processing large-scale PC data is a significant challenge. PCs can contain a vast number of points, especially in complex or large-scale environments. Processing and analyzing such datasets require efficient algorithms and significant computational resources. Super-resolution techniques need to be scalable and computationally efficient to handle large

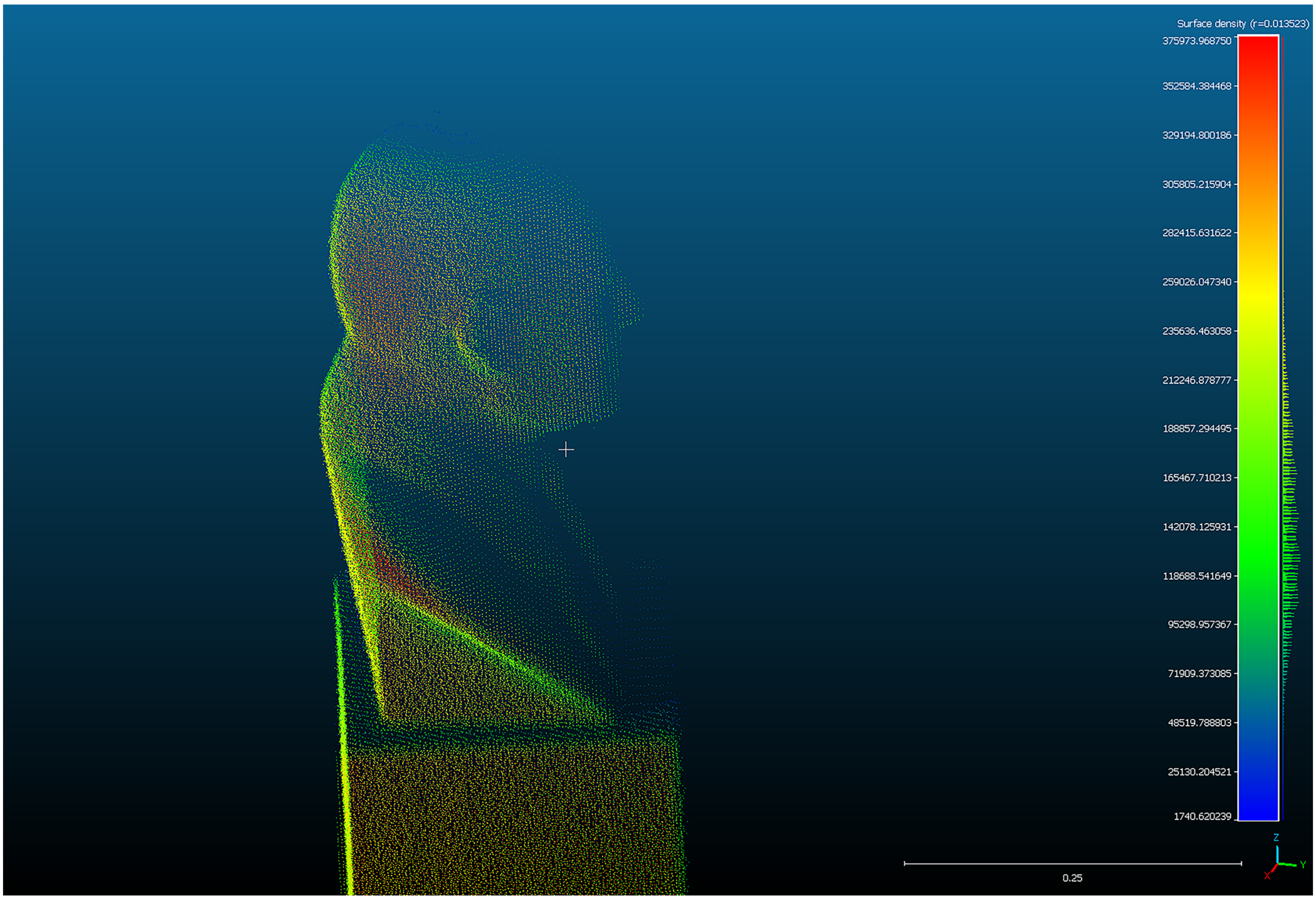

Fig. 1 Incomplete representation

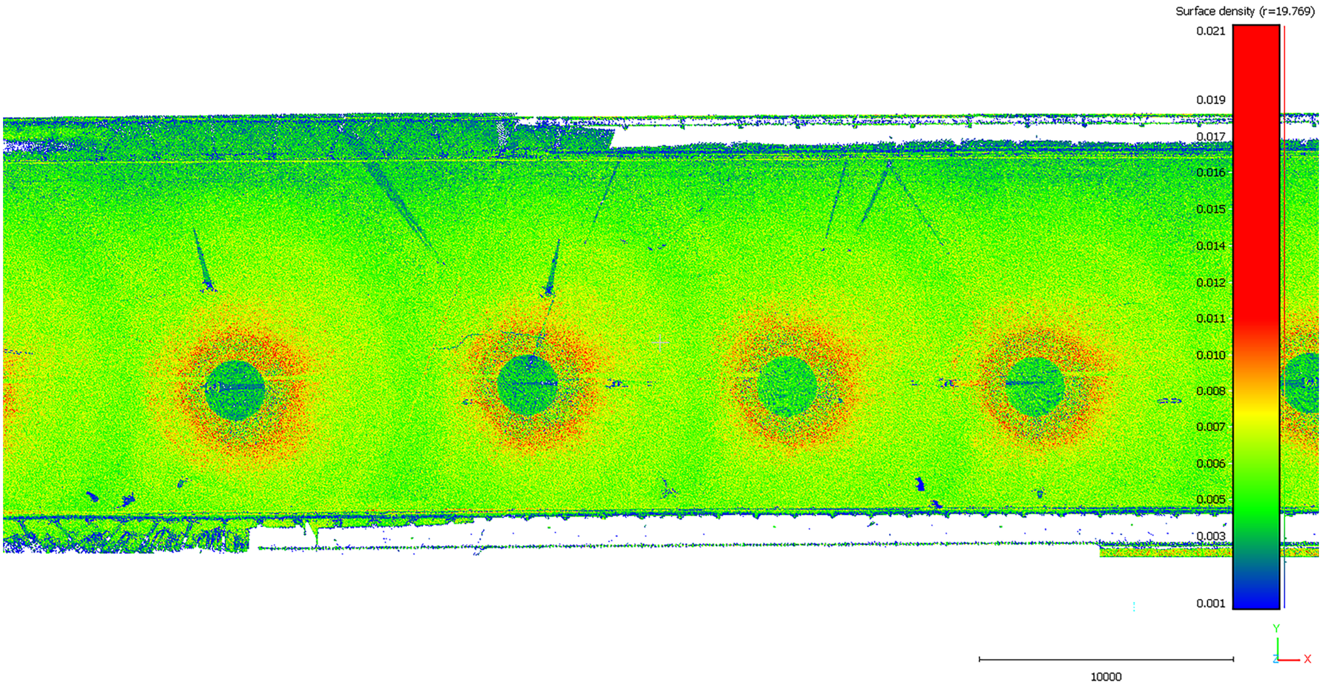

Fig. 2 Uneven density

PCs in real-time applications. Upsampling methods play a crucial role in addressing the aforementioned challenges and unlocking the full potential of PC data. By enhancing the level of detail and resolution, super-resolution enables more accurate and comprehensive analysis, visualization, and reconstruction of 3D scenes [48, 49].

3 Point cloud upsampling methodologies

3.1 Non-deep-learning based upsampling methods

Numerous publications in PC upsampling established the groundwork for subsequent researches. The pioneering work of Alexa et al. [50] suggested increasing the density of point clouds by creating a Voronoi diagram on a smooth moving least squares (MLS) surface and placing points at the diagram's vertices. This technique depends on the assumption that the surface is smooth in order to interpolate points efficiently. Denser point cloud representations were achieved by placing points at the vertices of a structured Voronoi diagram. Later, Lipman et al. [51] published a new operator called locally optimal projection (LOP) that is a parameterization-free method for point resampling and surface reconstruction. This technique effectively estimates surfaces in point cloud data and can increase the density of the starting points by carrying out multiple LOP iterations. By utilizing the L1 norm, the LOP operator efficiently samples and rebuilds surfaces. This model was extended by Huang et al. [52] introducing a weighted version of the locally optimal projection (WLOP) operator, which improves the original LOP by incorporating local density weights for a more evenly distributed point cloud. This enhanced WLOP operator is more capable of managing sharp edges, outliers, and non-uniformity, overcoming some constraints of LOP when dealing with smooth surfaces. Huang et al. [53] introduced the edge-aware resampling method (EAR) for point cloud upsampling. It involves initially resampling points based on normal information, moving them away from edges, before gradually upsampling points near edge singularities. EAR adds position and normal details to ensure the operator is symmetrical and sensitive to edges, maintaining crisp features while being resistant to interference. Yet, the effectiveness of EAR is greatly influenced by the provided baseline data and adjustment of parameters. Preiner et al. [54] introduced a variation of the weighted locally optimal projection operator called Continuous LOP (CLOP). CLOP employs a Gaussian mixture model for representing the density of the input point cloud, which enables quick and effective surface reconstruction. This method is appropriate for producing a PC representation that is more compact and seamless. Wu et al. [55] introduced a successful deep point representation method aimed at filling in large gaps in PC data, but the lack of global smoothness enforcement made it sensitive to noise. Dinesh et al. [38] suggested a method for enhancing 3D PCs by utilizing graph total variation (GTV) with surface normals. New points were created at the centroids of the triangles formed by Delaunay triangulation, while maintaining the original 3D coordinates. The issue was resolved through a GTV optimization technique using the alternating method of multipliers (ADMM) and proximal gradient (PG) methods. The validity of the method was confirmed using Stanford 3D data [56], showing improved PC resolution without sacrificing geometric accuracy through point-to-point and point-to-plane metrics. Also, Dinesh et al. [57] proposed a graph total variation approach for enhancing the resolution of colored PCs by utilizing a voxelized PC. Borges et al. [58] introduced a PC upsampling technique named SRLUT that leverages self-similarity in the PC. This method utilizes lookup-tables (LUTs) to connect a voxel's downsampled neighborhood with its children's occupancy for achieving super-resolution at any fractional scale. Assuming self-similarity across different scales, the technique predicts child occupancy using downscaled iterations of one input PC, resulting in improved outcomes compared to methods such as nearest-neighbor interpolation [58].

3.2 Deep-learning based upsampling methods

Deep learning approaches have revolutionized the field of PC upsampling by leveraging the power of DL models. With their ability to learn complex patterns and relationships from large-scale datasets, these techniques have shown remarkable success in enhancing the resolution and level of detail in 3D PC data. DL techniques in the field of 3D vision signify a significant shift towards developing neural networks capable of autonomously extracting data to enhance the quality of upsampling processes from initiation to completion. This trend underscores the increasing focus on leveraging sophisticated algorithms to improve the accuracy and efficiency of reconstructing high-resolution 3D. Pioneer approaches to deal with PC upsampling were brought in by groundbreaking studies such as PU-Net [33] and EC-Net [59]. Yu et al. [33] introduced PU-Net, which utilizes the PointNet++ framework to capture diverse scale features for individual points and expands the point cloud through multi-branch MLPs, leading to the conversion of sparse point clouds into dense ones. Despite PU-Net surpassing previous optimization-driven techniques, its reliance on downsampled input results in an unnecessary reduction in resolution, resulting in point clouds lacking sharp edges and potentially introducing inconsistencies due to the neglect of spatial point relationships. However, the outcome frequently seems coarse and lacks well-defined boundaries when enlarged, leading to objects with uneven edges and irregular protrusions. This limitation arises from the need for PU-Net to decrease input size to capture multi-scale features, resulting in undesired resolution reduction and overlooking spatial relationships among points, potentially resulting in uneven sample distribution. Furthermore, PU-Net faced challenges during training because it did not leverage the similarities between low and high-resolution PC data when predicting point coordinates. Later, Yu et al.'s [59] EC-Net includes a combined loss that considers the proximity of points and edges to maintain edge clarity; however, it necessitates labeled edge and surface information for training. EC-Net was created to improve PC resolution by considering edges and using a combined loss function to preserve sharp edges, but it necessitates meticulous annotation of edge and surface data in the training phase. EC-Net focuses on detecting edges and reducing the distance between points and edges using an edge joint loss function. Yet, the approach is limited due to the need for costly edge annotations and extended training periods, making it impractical for extensive datasets.

Multi-Step Patch Upsampling (MPU) [60] replicates point patches at various stages and is recognized for its high computational cost because it advances step by step. Additional data is also required to monitor the outputs of the intermediate stage. However, MPU also employs a progressive upsampling method, but varies by utilizing varying numbers of neighbors in each subsequent upsampling unit. AR-GCN was introduced by Wu et al. [36], an initial endeavor to represent point cloud upsampling with a Graph Convolutional Network (GCN). AR-GCN considers each point and its surrounding points as an undirected graph, extracting local characteristics through graph convolution operations and enhancing point feature vectors to expand the points' quantity. Nevertheless, it is created for a specific increase in size during upsampling, requiring retraining for varying scales. The model employs residual graph convolution blocks and unpooling blocks to gradually increase the resolution of the point cloud, utilizing similarities between input and output point clouds to achieve quicker convergence and better performance.

Li et al. [61] presented PU-GAN, which is also a GAN to enhance the numerical outcomes of enlarged PCs. The primary innovation is found in the competitive structure, highlighting the importance of the discriminator in improving performance. A uniformity loss was introduced by PU-GAN to generate more uniform PCs, however it remains less effective with sparse and non-uniform input. Qian et al. [62] proposed PUGeo-Net; their network is designed to improve PC upsampling by training on local geometric features, estimating the augmented Jacobian matrix, and refining based on estimated tangent plane normals. The first step in the process involves PU-GeoNet parameterizing the 3D surface to a 2D domain, followed by sampling within the parametric domain, and ultimately mapping the 2D samples back to the 3D surface. Nevertheless, their approach necessitates further oversight via typical estimation. PUGeo-Net employs a distinct up-down-up module for adjusting features and starts by creating points in 2D space before converting them to 3D space. Qian et al. [63] presented PU-GCN, using graph-based network to improve the aggregation of locally multi-scale point information for cloud sampling purposes. Their technique effectively integrates two GCN-based modules, Inception DenseGCN for feature extraction and NodeShuffle for feature expansion. Thus, the efficient encoding of local features and point generation with no supplementary resource is enabled. However, slightly coarse outputs may result from the potential sacrifice of some global PC structure information by the model.

Dis-PU [64] disentangles the upsampling process into two sequential sub-networks: a more concentrated generator for creating a rough PC and a spatial refiner for improving it. Even with both global and local refinement units, the end result usually appears too polished, leading to a lack of texture details. However, Dis-PU focuses on resolving this issue by separating upsampling tasks and reaching cutting-edge outcomes, although current approaches still depend on flawless, noiseless low-resolution PC inputs, restricting their effectiveness in point completion missions. MAFU [65] expands linear interpolation to generate additional points and utilizes an adaptable training approach to accommodate varying upsampling factors. MAFU uses linear approximation theory to interpolate nearby point coordinates and forecast offsets at individual points in order to reduce high-order approximation errors. Furthermore, MAFU creatively adjusts interpolation weights and high-order approximation errors using a minimal neural network to understand the local structure of the input point cloud and produce consistent points for the upsampling objective.

Ye et al. [66] introduced Meta-PU, a graph convolution network inspired by Meta-SR, which is widely used in single-image super-resolution. Meta-PU utilizes a meta-subnetwork to adapt weights in a residual graph convolution (RGC) and incorporates farthest point sampling (FPS). Meta-PU uses a combination loss function to guarantee that the resulting points are evenly distributed on the underlying geometry surface and are smoothly spread out, regardless of the scale factor. The results show that Meta-PU can handle various upsampling scales and performs better than current methods designed for particular scale factors. However, Meta-PU encounters obstacles like high computational demands, inefficiency with substantial point clouds, and unevenly distributed results with potential local gaps. In addition, instability and decreased efficiency may be caused by having to anticipate a large number of convolution weights during training, particularly with higher upscale factors. Luo et al. [67] designed PU-EVA that transforms point cloud upsampling by unlinking the upsampling rate from the network structure, allowing streamlined one-shot training for any rates with the use of edge vectors. The approach utilizes edge-vector-based affine combinations to achieve varying upsampling rates, utilizing neighboring connections and limiting approximation errors within second-order terms of Taylor's Expansion. However, PU-EVA is limited by network size and running memory, restricting the range of upsampling rates they can manage.

Zhao et al. [68] presented SSPU-Net, a self-supervised PC upsampling network that includes a neighbor expansion unit (NEU) which dynamically learns weights for point interpolation based on local geometric structures. The system also consists of a differentiable rendering unit (DRU) that converts the PC into multiple images, allowing for seamless training from start to finish. In order to facilitate self-supervised learning, shape-consistent and image-consistent losses were implemented, which guarantee that the resulting dense PC retains identical 3D shapes and local geometric structures as the original input. Liu et al. [69] presented a methodology called PU-Refiner, which uses GAN architecture, working step-by-step from coarse to fine. The generator includes a feature expansion module for coarse features, a module for generating geometric shapes from coarse point clouds, and a refinement module for creating dense point clouds. The discriminator helps the generator create detailed point clouds with high resolution by using various levels of features, improving the quality and precision of the enlarged PC data.

PU-Dense, developed by Akhtar et al. [70], utilizes a unique feature extraction module to extract PC data and a multi-scale U-Net structure with sparse convolutions for efficacious PC upsampling. It fixes PC data by creating many points and removing superfluous points, surpassing methods based on voxel convolution. Nevertheless, indicating areas that could be enhanced, PU-Dense does not examine varying density properties of compressed point clouds or changes in density during processing. SAPCU by Zhao et al. [71] utilizing implicit neural representation, allowing for self-supervised and flexible upsampling at any scale. The approach transforms upsampling into locating the closest projection points on a hidden surface for initial points, using two neural networks trained without accurate dense PCs. The method has been proven through experiments to generate dense PC data that are high in quality, uniform, and complete. It attains competitive goal accomplishment and superior visual outcomes when compared to top supervised methods available. Liu et al. [72] presented SPU-Net, the method that employs a rough-to-precise reconstruction approach to efficiently extract and expand point features, and also utilizes self-projection optimization to improve upsampling quality by projecting noisy points onto the object's surface. This self-attention module is integrated with a network of graph convolution. Zhou et al. [73] introduced the ZSPU, a network inspired by ZSSR [74] that was designed for single-image Super-Resolution (SR). The self-aware representation of the complete point cloud is internally acquired using the ZSPU technique. This approach involves training the network from the scratch during testing by using augmented pairs of sparse-dense point clouds from the test data, eliminating the need for complicated setup and patch preprocessing like patch-based methods. Although ZSPU effectively utilizes internal characteristics, it has a lengthy inference time and does not use data from external datasets. ZSPU applies this internal learning method to point cloud upsampling, performing well in addressing areas with high curvature and producing strong results on standard datasets.

PU-Flow by Mao et al. [75] leverages normalizing flows (NFs) and weight prediction techniques. Using the invertible nature of NFs, the method can transform PCs between Euclidean space and latent distribution in a lossless manner. Upsampling is formulated as a local ensemble of latent variables, with interpolation weights learned adaptively from the local neighborhood. While it demonstrates high-quality results, limitations include handling non-uniform data and inferring global shapes. Liu et al. [76] introduced PUFA-GAN, a GAN that is conscious of frequency for upsampling 3D point clouds, aimed at producing dense point cloud data on the surface below by effectively reducing high-frequency noise. The generator consists of three components: a feature extraction module using dynamic graph hierarchical residual aggregation (DGHRA) for acquiring descriptive features at the point level, a feature expansion module based on cascaded hierarchical residual aggregation (HRA) to enhance feature intricacies, and a geometry generation module for translating features back to the geometry domain. The frequency-aware discriminator, consisting of a global discriminator and a high-frequency discriminator, enhances the quality of upsampled PC data by taking into account overall context to enhance skeleton recognition and reduce high-frequency noise. Furthermore, any potential noise is specifically eliminated while testing with the use of a graph filter.

PU-Transformer, the initial transformer model developed by Qiu et al. [77] for upscaling point clouds, showcases substantial enhancements both quantitatively and qualitatively compared to leading CNN-based approaches on different datasets. It displays excellent performance by successfully competing with top methods across various benchmarks. He et al.'s [78] network, presented Grad-PU, a method that interpolates a lower-resolution point cloud and enhances it through iterative optimization, enabling the use of any upsampling rates. This method uses a trained model to predict variances between interpolated and high-resolution target points. It utilizes the midpoint algorithm within neighborhood features; this network also attains great results because it converts the upsampling task into a problem of approximating coordinates, eliminating the necessity for designing explicit upsampling modules. Zhong and Bai [79] utilized PSR-GAT as a method for improving PC upsampling through utilizing local geometric characteristics. The method presents the P-GAT model, allowing for unlimited-scale super-resolution using a single model through meta-learning. It utilizes both residual connections and a graph attention network to merge different levels of features, decrease network deterioration, and enhance the quality of point cloud generation. Experimental results from benchmark datasets demonstrate that PSR-GAT attains the highest level of performance. Kumbar et al. [80] published ASUR3D a method for upsampling 3D PC data at any scale by utilizing Local Occupancy Representation and a trigonometric feature extractor as a universal surface approximator. ASUR3D, in contrast to traditional deep networks, employs the marching cube algorithm for effectively increasing the resolution of PCs at specified speeds using only one trained model. ASUR3D surpassed current methods in analyzing heritage data, proving its accuracy and efficiency in practical scenarios.

PU-SSAS by Zhao et al. [81] describes PC upsampling as locating the closest projection points on an implicit surface for seed points by employing two implicit neural functions trained via pretext learning activities. The technique is adaptable in terms of magnification, enabling training just once to tackle different scaling factors, and it is the initial method to merge self-supervised learning with upsampling at any scale. Zhao et al. [82] introduced APUNet a method that utilizes DisTransformer to simulate relationships between points while considering distance limitations. A network for extracting features combines patch and point correlations for overall object representation. An initial PC is optimized by a point set prediction module to generate an upsampled cloud, avoiding nearby points. This method changes from expanding features to predicting features, enhancing performance on sparse and non-uniform point clouds. Li et al. [83] introduced PU-CTG, which extract and integrate features across multiscale blocks efficiently, with the use of position encoding to assist in learning spatial relationships. The system uses a hierarchical upsampling technique before applying a 2D grid to improve feature variety and optimize point creation. The advanced DCD loss is employed in the training process to guarantee that created points match the desired surface. Results from experiments demonstrate that PU-CTG boosts upsampling and improves performance in classifying point clouds. Liu et al. [84] introduced PU-Mask an innovative method for upsampling PC that approaches the task as a problem of "local filling". A virtual mask is applied to each point, then filled with an auto-encoder to predict local point distribution and finally refined using a pseudo-Laplacian operator. PU-Mask excels over other methods by generating high-quality PC data that are evenly distributed and free of local noise or geometric inconsistencies, making it a top choice for surface reconstruction projects.

PU-Ray by Lim et al. [85] tackle the domain dependency issue of current end-to-end PC upsampling methods. PU-Ray utilizes the sphere tracing algorithm with a neural implicit surface to accurately predict depth for rays being queried. It creates a varying number of inquiry rays through an innovative rule-driven method that tackles the problem of uneven distribution, making use of trained models with reconstruction loss functions based on nearest neighbors. The approach also utilizes precise ground truth information for training in supervised and self-supervised learning, making it appropriate for real-world Intelligent Transportation Systems (ITS) situations. Very recently, RE-PU by Han et al. [86], an innovative method for increasing PC density using self-supervised PC reconstruction, has been able to increase density at any desired rate. The process involves two steps: first, training a model with original PC data and a prior distribution, and second, increasing the number of sampled points through upsampling with the trained model. The research emphasizes the significance of dynamic graph and offset attention components, along with the influence of previous distributions on network effectiveness. In the future, research will investigate how point cloud reconstruction is related to upsampling, and how it can be applied in completing and generating point clouds.

3.3 Systematic classification of upsampling methods

In Section 3.2, we have introduced non-deep-learning and deep-learning-based upsampling methods for point clouds. Based on the detailed description, it is obvious that a consistent classification based on common features should be established, and then the described methods should be classified accordingly. In total, 40 methods were subjected to a thorough analysis, and then, by progressively refining the classifications, five main categories were established. Sections 3.1 and 3.2 described the classification of methods based on traditional (non-deep learning) and artificial intelligence (deep learning). In Section 3.3, we have categorized them according to the technology implemented by the algorithms of the methods. Table 1 summarizes and illustrates the five main groups that have been established and which procedures are operational according to each aspect. For ease of reading and retrieval, references to the methods in the literature are included.

4 Conclusions

In summary, after a thorough review of the literature in the field, it can be stated that deep learning methods appeared after the initial statistical methods, which proved to be pioneering in the development of the scientific field. DL processes can be grouped according to their architectures. Based on this, PC upsampling seems to be dominant in three main directions in the future. The solutions relying on feature learning are likely to be the most prominent. Improved feature extraction solutions are credited for the advancement of deep learning networks in computer vision (CV). The feature processes consist of two main parts: the layers for extracting numerous features and the final classification neural network in the network structure.

The second component is a basic neural network designed for classification, which plays a crucial role in computer vision (CV) tasks. The feature processes consist of two main parts: the layers for extracting numerous features and the final classification neural network in the network structure. The second one is a basic neural network that is simple and has complete connectivity. Nevertheless, as CV evolved, the number of layers preceding it grew, leading to the emergence of increasingly intricate structures, resulting in the gradual enhancement of recognition capabilities in feature method networks in recent years. Based on our assumption, we can anticipate a similar development curve in advancing upsampling techniques based on feature extraction. Another potential approach in PC upsampling is GAN and graph networks. Significant progress in GAN technology has been evident, with the emergence of new versions like Conditional GAN (CGAN), Deep Convolutional GAN (DCGAN), Wasserstein GAN (WGAN), and Mutual Information GAN (MIEGAN).

Significant advancements like DALL-E in image generation applications illustrate notable progress in this field, building on past innovations. The ongoing advancement in GAN technology has the immense potential to change the field of image production. In tasks such as PC upsampling, the ability of generative network models in the GAN framework to create high-quality images is vital, leading to promising results for future applications. Combining the advancing abilities of the GAN model with the upscaling procedure could potentially lead to a significant increase in performance in the near future, ultimately paving the way for improved image generation methods and uses. The combination of GAN and graph technologies forms a strong synergy that is expected to expand the limits of what can be accomplished in the exciting realm of artificial intelligence and image processing. The third category, Edge-Aware Methods, holds lesser potential but is still noteworthy. Edge-aware networks are planned to tackle these particular difficulties by integrating edge data into the upsampling process. Utilizing the knowledge of edge patterns in the PC, these networks help produce more precise and detailed points during the upsampling process. Edge-aware networks are a major step forward in PC upsampling technology, tackling the key issue of maintaining intricate geometric features and edges. These networks achieve excellent performance by including edge information in the upsampling process, which is crucial for applications needing detailed 3D representations.

There is great potential in the future of edge-aware networks for PC upsampling, with anticipated improvements in algorithm efficiency, real-time processing, reliability, and integration with various data modalities. These advancements will enhance the quality and usability of upsampled PCs as well as broaden their usage in

Table 1 Clustering point cloud upsampling methods

Cluster	Technology	Methodology
Surface and projection-based methods	Voronoi diagram [50]	Surface-based
	LOP [51]	Projection-based
	WLOP [52]	Enhanced projection-based
	CLOP [54]	Continuous
	GTV [38, 57]	Surface-based
	SAPCU [71]	Neural representation
	PU-SSAS [81]	Implicit neural functions
	PU-Ray [85]	Sphere tracing algorithm
Edge-aware methods	EAR [53]	Edge-aware
	EC-Net [59]	Edge-aware learning
	PU-EVA [67]	Edge-vector based
	SRLUT [58]	Self-similarity
Feature learning and upsampling methods	PU-Net [33]	Multi-scale feature learning
	MPU [60]	Progressive upsampling
	Dis-PU [64]	Progressive upsampling
	Meta-PU [66]	Arbitrary-scale upsampling
	MAFU [65]	Linear approximation
	Grad-PU [78]	Gradient descent
	PU-Dense [70]	Sparse tensor-based
	PU-Transformer [77]	Transformer-based
	PU-Flow [75]	Flow-based
	ASUR3D [80]	Local occupancy representation
	SSPU-NET [68]	Neighbor expansion
	APUNet [82]	DisTransformer
Graph and GAN-based methods	AR-GCN [36]	Graph convolution
	PU-GCN [63]	Graph convolution
	PU-GAN [61]	GAN-based
	PU-Refiner [69]	GAN-based
	PUFA-GAN [76]	Frequency-aware GAN
	PSR-GAT [79]	P-GAT model
	RE-PU [86]	Offset attention component
Specialized and hybrid methods	Deep point representation [55]	Gap-filling
	PUGeo-Net [62]	Geometry-centric
	SPU-NET [72]	Hierarchical folding
	ZSPU [73]	Zero-shot learning
	PU-CTG [83]	2D grid
	PU-Mask [84]	Pseudo-laplacian operator

different industries, resulting in notable technological and societal advantages. It should be noted that current traditional Convolutional Neural Networks (ConvNets) do not significantly impact upsampling point cloud data processing. This restriction is a result of the pooling operations being computationally intensive for processing three-dimensional data. The complexity of pooling in a three-dimensional space makes it difficult for traditional ConvNets to manage PC upsampling tasks, leading to this problem effectively. The failure to incorporate ConvNets in this particular task exposes a deficiency in the current methods for manipulating PC data. The efficiency and effectiveness of ConvNets for upsampling are often limited by the high computational demand of pooling operations in 3D space. Recently, there has been a significant increase in the number of networks being published in the field, leading to a call for a detailed examination of the impacts of upsampling methods. Thus, it would be advantageous and pertinent to carry out a thorough comparative analysis to measure the results obtained from utilizing upsampling techniques. With the network architecture evolving rapidly and data analysis tasks becoming more complex, it will be essential to assess the effects and efficacy of upsampling on network performance to guide future research efforts. By methodically examining the outcomes of various upsampling methods, and researchers can understand how these techniques impact network performance and capacity to deal with different data types. This comparative analysis will not just provide insight into the advantages and constraints of upsampling, but also enhance comprehension of the significance of data augmentation in network training and validation. In the end, this research will open the door for better approaches and tactics in designing networks, resulting in stronger and more precise models that can address the challenges of various datasets and real-world scenarios more effectively.

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