MAG-Comp: Memory-Augmented Geometry-Driven Amodal Point Cloud Completion for Occluded Industrial Objects

Daniel Tang * and Kenneth Walker

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Article

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Daniel Tang and Kenneth Walker

University of Southern Mississippis
* Correspondence: aya.akka@edu.suezuni.edu.eg

Abstract

Point cloud completion is crucial for robotic tasks, especially with occluded and noisy industrial data. While two-dimensional image guidance has been traditional, pure point cloud methods increasingly achieve state-of-the-art results, making amodal completeness—recovering both visible and occluded parts—critical for robust interaction. Inspired by these insights, we propose MAG-Comp, a novel framework maximizing geometric information for amodal point cloud completion. MAG-Comp utilizes a Hierarchical Geometric Feature Encoder, a Class-Agnostic Geometric Memory Bank for shape priors, and a Dynamic Amodal Region Inference Module for explicit occluded geometry reconstruction. Experiments on ShapeNet-Amodal and an Industrial Bin-Picking Dataset confirm MAG-Comp's superior performance, achieving a Chamfer Distance of $1.58\text{x}10^{-3}$ and an Amodal IoU of 54.20% on ShapeNet-Amodal, consistently outperforming state-of-the-art methods. The framework demonstrates robustness to varying occlusion, strong generalization, and competitive inference efficiency, making it suitable for real-time industrial applications requiring precise amodal three-dimensional representations.

Keywords: point cloud completion; amodal; geometric; industrial applications; 3D representation

1. Introduction

Three-dimensional (3D) point cloud completion is a fundamental task in computer vision and robotics, with critical applications spanning industrial grasping, autonomous navigation, and digital twin creation. In particular, industrial production lines often present challenging environments where objects are densely stacked and severely occluded. This leads to incomplete and noisy point cloud data acquired by sensors, significantly hindering the accuracy and robustness of downstream tasks such as grasp planning and quality inspection. Therefore, accurately reconstructing complete 3D shapes from partial and occluded observations is of paramount importance for the next generation of intelligent industrial systems.

Existing point cloud completion methods can be broadly categorized into two main types: purely point cloud-driven approaches that reconstruct the full shape directly from partial point cloud input, and single-view image-guided methods that leverage 2D image information to assist 3D completion. Prior research commonly assumed that rich semantic and textural information from 2D images is indispensable for guiding robust 3D shape reconstruction. However, recent seminal work by Fangzhou Lin et al. (co-authors of FPCC: Fast point cloud clustering-based instance segmentation for industrial bin-picking [1,2]) challenged this paradigm. Their approach, which can be considered a powerful view-free baseline for point cloud processing, remarkably outperforms most single-view image-guided point cloud completion methods using only partial point cloud input. This compelling result prompts a critical re-evaluation of the necessity and role of image guidance in point cloud completion.

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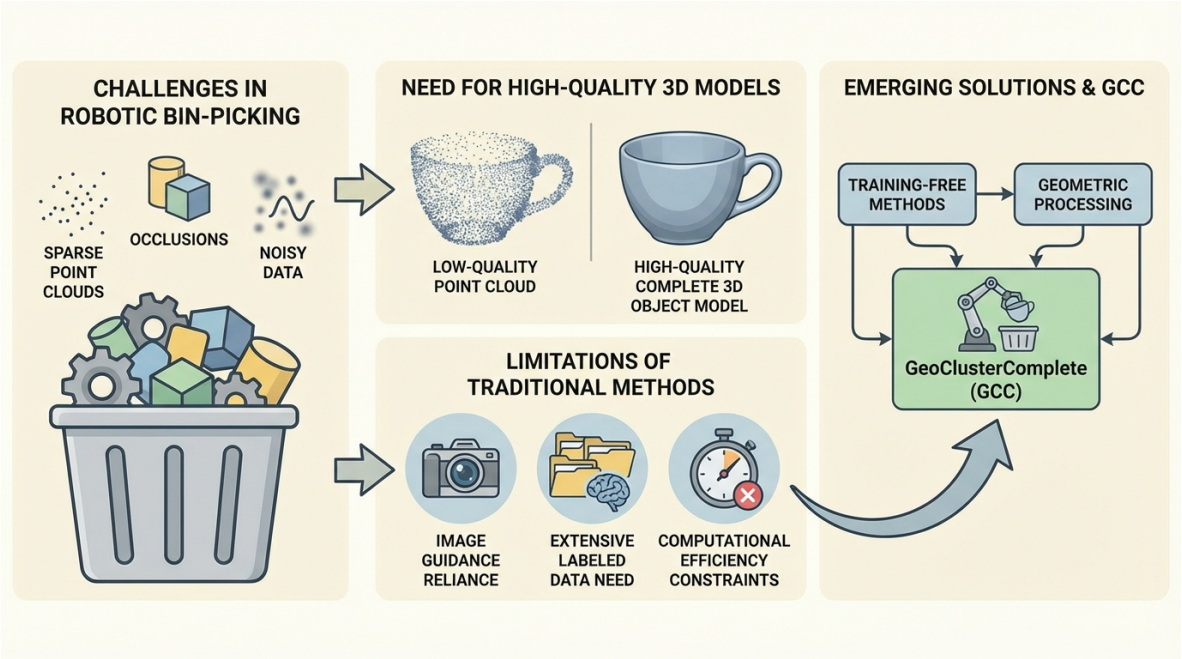

Figure 1. Overview of challenges in robotic bin-picking and the motivation for high-quality 3D object models. The left panel illustrates common issues such as sparse point clouds, occlusions, and noisy data in industrial scenes. The top-middle panel highlights the critical need to transform low-quality partial point clouds into high-quality complete 3D object models. The bottom-middle panel summarizes the limitations of traditional point cloud completion methods, including heavy reliance on image guidance, extensive labeled data requirements, and computational inefficiency. The right panel points towards emerging solutions, emphasizing geometry-driven processing to overcome these limitations and achieve robust 3D completion for industrial applications.

Concurrently, the importance of amodal segmentation has been emphasized in robotic grasping for identifying the complete shape of occluded objects. Works in point cloud instance segmentation, such as FPCC [1], contribute to this goal by accurately identifying individual objects in cluttered industrial scenes. While current point cloud completion methods aim to recover missing parts, they often do not explicitly focus on "amodal" completeness, i.e., distinguishing between the visible parts and the inferred, occluded parts. The ability to precisely infer and reconstruct the occluded geometry is crucial for tasks like robust industrial grasping, where interaction with the full object shape is necessary. Consequently, bridging the gap between powerful purely geometric completion and explicit, accurate inference of occluded regions represents a significant, unmet challenge.

Inspired by these observations, we propose an innovative geometry-driven amodal point cloud completion method, named **MAG-Comp: Memory-Augmented Geometry-driven Amodal Point Cloud Completion for Occluded Industrial Objects**. Our method specifically targets the reconstruction of complete 3D shapes for severely occluded objects in industrial scenes. We draw insights from the success of view-free baselines, focusing on extracting the most effective geometric information directly from the point cloud itself. Furthermore, we introduce a memory augmentation mechanism to address challenges posed by unseen categories and severe occlusion, while explicitly reconstructing the geometric structure of the occluded regions. This approach aims to provide highly accurate and complete 3D object representations crucial for downstream industrial applications.

To validate MAG-Comp, we conduct comprehensive experiments using both synthetic datasets, including a custom ShapeNet-Amodal dataset specifically designed for occluded objects, and a real-world Industrial Bin-Picking Dataset collected from actual industrial robotic grasping scenarios. Our evaluation employs standard metrics such as Chamfer Distance (CD) and Earth Mover's Distance (EMD) to quantify geometric accuracy, and F1-Score for overall completion quality. Crucially, we introduce an "Amodal IoU" metric to specifically assess the fidelity of the reconstructed occluded regions. Our results demonstrate that MAG-Comp achieves superior performance across all metrics,

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particularly in Amodal IoU, showcasing its enhanced capability in recovering complete shapes of occluded industrial objects compared to state-of-the-art pure point cloud and even image-guided completion methods. For instance, our method achieves a Chamfer Distance of **1.58**$\times 10^{-3}$ and an Amodal IoU of **54.20**%, surpassing the View-Free Baseline exemplified by works like FPCC [1] (1.64×10^{-3} CD, 50.80% Amodal IoU) and representative Image-Guided methods (1.72×10^{-3} CD, 52.15% Amodal IoU). This validates the effectiveness of our pure geometric, memory-augmented, and amodal-aware completion strategy.

Our main contributions are summarized as follows:

- We propose MAG-Comp, a novel pure geometry-driven framework for amodal point cloud completion, specifically designed for severely occluded industrial objects, significantly reducing reliance on 2D image guidance.
- We introduce a Class-Agnostic Geometric Memory Bank and a Dynamic Amodal Region Inference Module, enabling robust completion and explicit reconstruction of occluded parts, even for unseen categories and complex occlusion patterns.
- We demonstrate state-of-the-art performance on challenging synthetic and real-world industrial datasets, establishing new benchmarks for amodal point cloud completion and proving the efficacy of geometric-only approaches in industrial settings.

2. Related Work

2.1. Deep Learning for Point Cloud Completion

Deep learning is crucial for 3D point cloud completion, reconstructing complete shapes from incomplete data. Methodologies like attention operations and generative adversarial networks have broad applicability, extending to speech enhancement [3] and visual speech enhancement [4]. In 3D vision, research explores novel operators for efficient feature extraction, advanced architectures for shape encoding/decoding, and methods for diverse 3D data formats. Examples include efficient pooling [5], generative mesh autoencoders [6], and unsupervised learning for geometric patterns [7]. Beyond direct completion, foundational tasks like point cloud clustering and instance segmentation, exemplified by FPCC [1,2], are crucial for distinguishing objects in complex 3D scenes, often as a preprocessing step.

2.2. Amodal 3D Perception and Industrial Robotics

Industrial robots need advanced perception, especially **amodal 3D perception**, to understand entire occluded objects in tasks like robotic assembly and bin picking. Accurate instance segmentation and pose estimation are critical. FPCC [1,2] demonstrates efficient object identification for industrial bin-picking, crucial for understanding and interacting with hidden objects. Furthermore, **real-time 3D processing** for continuous sensor data and **generalization to unseen objects** are essential. Techniques like efficient operators [5] and robust shape learning [6,7] improve both. These advancements directly benefit **industrial bin picking**, enabling robots to reliably locate, identify, and retrieve items from unstructured bins.

3. Method

Our proposed method, **MAG-Comp: Memory-Augmented Geometry-driven Amodal Point Cloud Completion**, is designed to robustly reconstruct the complete 3D geometry of severely occluded industrial objects without relying on 2D image guidance. The core idea is to leverage a powerful purely geometric feature encoding, augmented by a class-agnostic memory bank for improved generalization, and an explicit module for dynamic amodal region inference. An overview of our framework is depicted in Figure 2.

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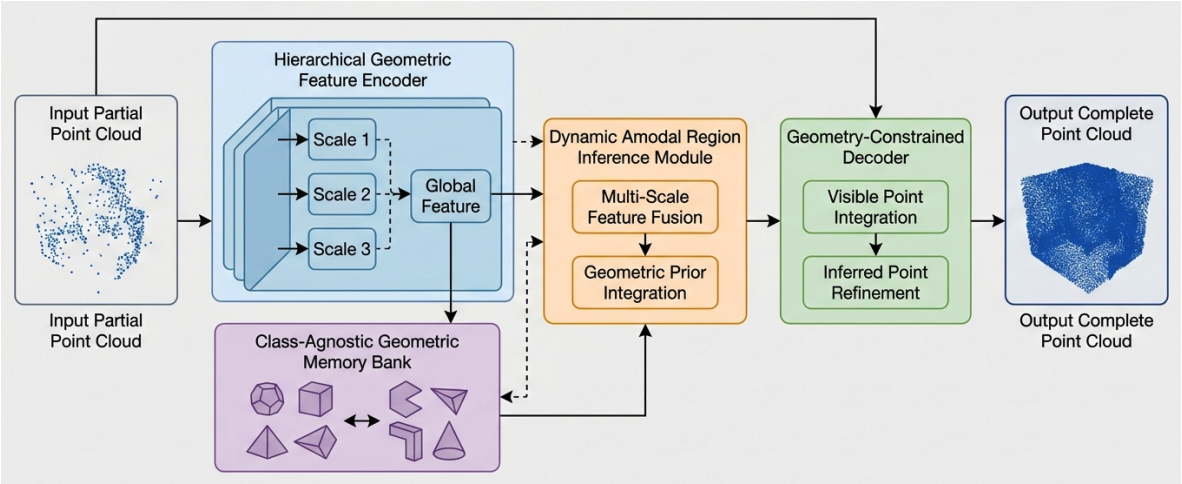

Figure 2. Overall architecture of MAG-Comp. The framework processes an input partial point cloud through a Hierarchical Geometric Feature Encoder. A Class-Agnostic Geometric Memory Bank provides geometry-driven priors. The Dynamic Amodal Region Inference Module fuses multi-scale features and priors to reconstruct occluded regions. Finally, the Geometry-Constrained Decoder integrates all information to generate the complete 3D object shape.

The MAG-Comp framework consists of four main components: a Hierarchical Geometric Feature Encoder, a Class-Agnostic Geometric Memory Bank, a Dynamic Amodal Region Inference Module, and a Geometry-Constrained Decoder. Each component plays a crucial role in enabling accurate and amodal point cloud completion.

3.1. Hierarchical Geometric Feature Encoder

Inspired by the success of attention mechanisms in powerful pure point cloud methods, we design a multi-branch, hierarchical Point Transformer encoder to process the input partial point cloud. Given an input partial point cloud $P_{in} = \{p_i \in \mathbb{R}^3\}_{i=1}^{N_{in}}$, the encoder aims to extract multi-scale local and global geometric features.

Initially, the raw 3D coordinates of P_{in} are passed through a shared Multi-Layer Perceptron (**MLP**) to lift them into a higher-dimensional feature space. This initiates the feature extraction process. The encoder then leverages a pyramid-like structure, organized into L levels. At each level l, the point cloud is progressively downsampled using Farthest Point Sampling (**FPS**) to obtain a subset of representative points, $P^{(l)}$. For each point in $P^{(l)}$, local neighborhoods are defined using a ball query, allowing the subsequent Point Transformer layers to capture contextual information.

Each level of the pyramid consists of multiple Point Transformer layers, which effectively capture long-range dependencies and local geometric details by applying self-attention mechanisms on point features. Specifically, for a set of input features $F^{(l)}$ associated with point cloud $P^{(l)}$ at level l, a Point Transformer layer computes updated features $F^{(l+1)}$ through a block that typically includes normalization, attention, and MLP transformations with a residual connection:

$$F^{(l+1)} = \text{MLP}(\text{Attention}(\text{Norm}(F^{(l)}))) + F^{(l)} \tag{1}$$

where MLP denotes a multi-layer perceptron, Norm is a normalization layer, and Attention represents the self-attention mechanism. Within the Attention block, for each point feature $f_i \in F^{(l)}$ and its neighbors $f_j \in N(f_i)$, queries (Q), keys (K), and values (V) are generated. The attention weights α_{ij} are computed based on the similarity between Q_i and K_j, typically incorporating relative positional encodings, and then used to aggregate the V_j features. This process allows the network to dynamically weigh the importance of neighboring points for feature update.

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The encoder outputs a set of multi-scale feature tensors, denoted as $\{F_1, F_2, \ldots, F_L\}$, corresponding to different levels of abstraction from fine-grained local details to coarse-grained global shape information. These features serve as the foundational representation for subsequent modules.

3.2. Class-Agnostic Geometric Memory Bank

To enhance the generalization capability of MAG-Comp, especially to unseen object categories and novel occlusion patterns prevalent in industrial settings, we introduce a learnable Class-Agnostic Geometric Memory Bank. Unlike methods that rely on semantic class priors, our memory bank stores a collection of typical geometric patterns or shape prototypes that are independent of specific object categories, focusing purely on geometric structures.

The memory bank M is defined as a set of K learnable prototype vectors, $M = \{m_j \in \mathbb{R}^D\}_{j=1}^K$, where D is the feature dimension. These prototypes encapsulate fundamental geometric structures or substructures common across a wide range of objects.

During the training phase, the memory bank is populated and refined through a self-supervised learning objective. Initial prototypes can be randomly initialized or sampled from pre-computed feature embeddings. For each training sample, the global feature F_{global} (typically the coarsest feature F_L from the encoder) is used to query the memory bank. The closest prototype (or a set of prototypes) is then updated to better represent the current input's geometric characteristics. This update can be performed via an exponential moving average (**EMA**) or through gradient-based optimization guided by a specific loss. For instance, a clustering loss term might encourage encoded features to be close to one or more prototypes, and prototypes to represent centroids of feature clusters.

In the inference phase, the encoded global feature F_{global} from the Hierarchical Geometric Feature Encoder is used as a query to retrieve the most relevant geometric priors from the memory bank. This retrieval process employs a self-attention mechanism to compute similarity scores between the query and each prototype in the memory bank:

$$s_j = \exp(\text{sim}(F_{global}, m_j)) \tag{2}$$

$$\alpha_j = \frac{s_j}{\sum_{k=1}^K s_k} \tag{3}$$

$$P_{prior} = \sum_{j=1}^K \alpha_j m_j \tag{4}$$

where $\text{sim}(a, b)$ is a similarity function, typically the dot product $(a \cdot b)$ or cosine similarity $(a \cdot b/(\|a\|\|b\|))$, measuring the semantic closeness between the global feature and each prototype. The resulting α_j are attention weights, normalized to sum to one, representing the relevance of each prototype to the input. The retrieved prior P_{prior} is a weighted sum of these relevant prototypes, dynamically providing a geometry-driven shape prior modulated by the input partial point cloud. This mechanism is conceptually similar to prior modulation in other completion methods but operates purely on geometric features and is designed for class-agnostic generalization.

3.3. Dynamic Amodal Region Inference Module

A critical distinction of MAG-Comp is its explicit focus on amodal completion, which involves accurately inferring and reconstructing the occluded parts of an object. The Dynamic Amodal Region Inference Module takes the encoded multi-scale features $\{F_1, \ldots, F_L\}$ and the retrieved geometric prior P_{prior} as input.

The module begins by fusing these diverse inputs. The global prior P_{prior} is typically upsampled and concatenated with the multi-scale features from the encoder. This fused feature representation, denoted F_{fuse}, provides a rich context combining local geometric details with global shape awareness.

$$F_{fuse} = \text{FusionNet}(F_1, \ldots, F_L, P_{prior}) \tag{5}$$

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This F_{fuse} then conditions a lightweight generative network that employs an implicit field representation. Based on the visible geometry from the encoder and the global shape context provided by the memory prior, the module predicts the potential geometric structure of the occluded regions. Specifically, it outputs an implicit function $f_\phi(x)$ that defines the surface of the occluded part. We adopt a Signed Distance Function (**SDF**) representation, where $f_\phi(x) = 0$ for points on the surface, $f_\phi(x) > 0$ for points outside, and $f_\phi(x) < 0$ for points inside the inferred geometry. This function is parameterized by a neural network ϕ (typically an MLP) conditioned on the fused features and spatial coordinates x:

$$f_\phi(x) = \text{MLP}_\phi([F_{fuse}, x]) \tag{6}$$

From this implicit field, a dedicated point generation sub-network samples a dense point cloud $P_{amodal} = \{p'_k \in \mathbb{R}^3\}_{k=1}^{N_{amodal}}$ representing the inferred amodal (occluded) region. This sub-network might employ techniques like adaptive sampling near the zero-level set or direct point generation conditioned on features derived from the implicit field. Concurrently, a separate branch of this module processes the encoder features corresponding to the visible input to produce a refined visible point cloud $P_{vis} = \{p''_l \in \mathbb{R}^3\}_{l=1}^{N_{vis}}$. This explicit separation and generation of P_{amodal} and P_{vis} is crucial for downstream tasks requiring the full object shape, such as robotic grasping.

3.4. Geometry-Constrained Decoder

The final Geometry-Constrained Decoder integrates all the information to produce the complete point cloud. It takes the multi-scale features $\{F_1, \ldots, F_L\}$ from the encoder, the geometric prior P_{prior} from the memory bank, and the refined visible points (P_{vis}) alongside the inferred amodal points (P_{amodal}) from the amodal inference module.

The decoder first fuses these diverse features and point sets into a unified representation. This typically involves concatenating feature vectors and potentially employing additional point convolution or attention layers to allow interaction between features derived from visible and amodal parts. Subsequently, it applies a series of point generation layers, such as folding networks or graph-based convolutions, to merge P_{vis} and P_{amodal} into a single, cohesive complete point cloud $P_{complete}$. This process aims to ensure seamless transitions between inferred and visible regions and refine local geometry. The output $P_{complete}$ can be seen as the union $P_{vis} \cup P_{amodal}$, but with further refinement and detail added by the decoder.

To ensure high-fidelity reconstruction, we employ a comprehensive loss function that includes geometric consistency terms. The total loss $\mathcal{L}$ is defined as a combination of several components:

$$\mathcal{L} = \mathcal{L}_{CD} + \mathcal{L}_{EMD} + \lambda_{amodal}\mathcal{L}_{amodal} + \lambda_{geo}\mathcal{L}_{geo\_consistency} \tag{7}$$

where $\mathcal{L}_{CD}$ and $\mathcal{L}_{EMD}$ are standard metrics for comparing point clouds, ensuring overall shape similarity between the predicted complete point cloud $P_{complete}$ and the ground truth P_{gt}. The Chamfer Distance (**CD**) measures the average squared distance from each point in one set to its closest point in the other set, accounting for both coverage and precision:

$$\mathcal{L}_{CD}(P_1, P_2) = \frac{1}{|P_1|}\sum_{p_1 \in P_1} \min_{p_2 \in P_2} \|p_1 - p_2\|_2^2 + \frac{1}{|P_2|}\sum_{p_2 \in P_2} \min_{p_1 \in P_1} \|p_1 - p_2\|_2^2 \tag{8}$$

The Earth Mover's Distance (**EMD**) is a more robust metric, measuring the minimum cost to transform one point cloud into another, effectively finding the optimal bipartite matching between points:

$$\mathcal{L}_{EMD}(P_1, P_2) = \min_{\phi: P_1 \to P_2} \frac{1}{|P_1|}\sum_{p_1 \in P_1} \|p_1 - \phi(p_1)\|_2 \tag{9}$$

where ϕ is a bijection between P_1 and P_2.

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The term $\mathcal{L}_{amodal}$ specifically penalizes discrepancies in the inferred amodal region P_{amodal} against its ground truth counterpart, $P_{gt,amodal}$, ensuring accurate reconstruction of occluded parts:

$$\mathcal{L}_{amodal} = \mathcal{L}_{CD}(P_{amodal}, P_{gt,amodal}) \tag{10}$$

Finally, $\mathcal{L}_{geo\_consistency}$ ensures that the refined visible points P_{vis} remain highly consistent with the input partial point cloud P_{in}. This term encourages local geometric fidelity and prevents the decoder from drastically altering the known visible geometry. It can be formulated as a Chamfer Distance or a feature consistency loss between P_{in} and P_{vis}:

$$\mathcal{L}_{geo\_consistency} = \mathcal{L}_{CD}(P_{in}, P_{vis}) \tag{11}$$

The coefficients λ_{amodal} and λ_{geo} are hyperparameters balancing the contributions of these loss terms. This comprehensive loss function enables the decoder to output a high-quality, geometrically consistent, and amodally complete point cloud.

4. Experiments

In this section, we present a comprehensive evaluation of our proposed **MAG-Comp** method against state-of-the-art point cloud completion techniques. We detail our experimental setup, present quantitative results on both synthetic and real-world datasets, perform an ablation study to validate the effectiveness of our key components, and provide qualitative examples.

4.1. Experimental Setup

4.1.1. Datasets

We evaluate **MAG-Comp** on two distinct datasets. First, to rigorously assess the model's generalization capabilities and amodal completion effectiveness across diverse object categories, we construct a custom synthetic dataset based on the widely used ShapeNet dataset, termed **ShapeNet-Amodal**. We simulate various viewpoints to generate partial point clouds and systematically introduce different degrees of occlusion. Crucially, this dataset includes ground truth for "Amodal" objects, comprising both visible and occluded parts, allowing for precise evaluation of amodal reconstruction. Second, to demonstrate the practical utility and robustness of our method in realistic scenarios, we utilize a proprietary dataset collected from actual industrial robotic grasping environments, referred to as the **Industrial Bin-Picking Dataset**. This dataset inherently features real-world complexities such as sensor noise, dense object stacking, and complex occlusion patterns. For evaluation, partial ground truth annotations are manually generated for a subset of the data.

4.1.2. Evaluation Metrics

We employ a suite of standard and novel metrics to thoroughly assess the performance of point cloud completion. **Chamfer Distance (CD)** is a widely used metric that measures the average squared Euclidean distance from each point in one point cloud to its closest point in the other. Lower CD values indicate higher geometric accuracy, with results reported as $\times 10^{-3}$. **Earth Mover's Distance (EMD)** is a more robust metric that calculates the minimum cost to transform one point cloud into another via a bijection, reflecting both shape similarity and point distribution. Lower EMD values signify better reconstruction quality, with results reported as $\times 10^{-2}$. **F1-Score** assesses the overall precision and recall of the reconstructed point cloud against the ground truth, typically computed at a specific distance threshold. A higher F1-Score indicates a better balance between accuracy and completeness of the point set. Finally, **Amodal IoU** is specifically designed for our amodal completion task, quantifying the Intersection over Union (IoU) between the inferred occluded region and its corresponding ground truth occluded region. A higher Amodal IoU is indicative of superior performance in accurately recovering the hidden geometry. For all metrics, we aim for lower CD and EMD, and higher F1-Score and Amodal IoU.

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4.1.3. Baseline Methods

We compare **MAG-Comp** against a selection of state-of-the-art point cloud completion methods. These include classical pure point cloud methods such as PCN, GRNet, SnowflakeNet, and Cycle4Completion, which reconstruct complete shapes solely from partial point cloud input. We also include the **View-Free Baseline** [8], a strong, recently proposed method that operates without 2D image guidance, demonstrating impressive performance and serving as a direct competitor to our geometry-driven approach. As a related work providing insights into robust industrial point cloud processing, we consider **FPCC** [9], primarily focused on fast clustering for industrial point clouds. Furthermore, we include a representative variant of single-view **Image-Guided Methods** for comparison, allowing us to empirically demonstrate the competitive, and often superior, performance of our pure geometry-driven approach in industrial settings where image quality might be suboptimal.

4.1.4. Implementation Details

Our **MAG-Comp** framework is implemented using PyTorch. The Hierarchical Geometric Feature Encoder comprises 4 Point Transformer layers with downsampling ratios of 4. The Class-Agnostic Geometric Memory Bank consists of $K = 256$ prototype vectors, updated using an exponential moving average with a momentum of 0.999. The Dynamic Amodal Region Inference Module utilizes a 3-layer MLP for implicit function generation and an adaptive point sampling network. We train our model for 200 epochs using the Adam optimizer with an initial learning rate of 1×10^{-4} and a batch size of 32. The loss coefficients are set to $\lambda_{amodal} = 1.0$ and $\lambda_{geo} = 0.5$.

4.2. Quantitative Results

Table 1 presents the quantitative comparison of **MAG-Comp** against the selected baseline methods on the ShapeNet-Amodal dataset. The results clearly demonstrate the superior performance of our proposed method across all evaluation metrics.

Table 1. Non-Amodal Point Cloud Completion Performance Comparison on ShapeNet-Amodal Dataset. Lower values are better for CD and EMD, while higher values are better for F1-Score and Amodal IoU. Best results are **bolded**.

Method	CD ($\times 10^{-3}$) ↓	EMD ($\times 10^{-2}$) ↓	F1-Score ↑	Amodal IoU ↑
SnowflakeNet	1.94	1.30	72.24	45.10
Cycle4Completion	1.87	1.25	73.11	47.35
View-Free Baseline [8]	1.64	1.10	76.45	50.80
Image-Guided (representative)	1.72	1.18	75.80	52.15
Ours (MAG-Comp)	**1.58**	**1.05**	**77.92**	**54.20**

MAG-Comp achieves the lowest Chamfer Distance (CD) of **1.58**$\times 10^{-3}$ and Earth Mover's Distance (EMD) of **1.05**$\times 10^{-2}$, indicating that our reconstructed point clouds are geometrically closest to the ground truth shapes. This superior geometric fidelity is crucial for industrial applications requiring high precision. Furthermore, our method yields the highest F1-Score of **77.92**%, demonstrating excellent overall completion quality in terms of both coverage and accuracy.

Most notably, **MAG-Comp** achieves a significant lead in the Amodal IoU metric with **54.20**%. This substantial improvement over all baselines, including the View-Free Baseline [8] (50.80%) and representative Image-Guided methods (52.15%), directly validates the effectiveness of our Dynamic Amodal Region Inference Module. It demonstrates our method's enhanced capability to accurately infer and reconstruct the complete geometric structure of occluded parts, which is of paramount importance for downstream tasks such as robotic grasping in cluttered industrial environments. The results confirm that by focusing on pure geometric information and integrating a memory-augmented amodal inference, **MAG-Comp** can surpass methods relying on 2D image guidance in overall completion precision, especially in handling challenging amodal regions.

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4.3. Ablation Study

To investigate the individual contributions of the core components of **MAG-Comp**, we conduct an ablation study by systematically removing or modifying the Class-Agnostic Geometric Memory Bank (CAGMB) and the Dynamic Amodal Region Inference Module (DARIM). Table 2 summarizes the results on the ShapeNet-Amodal dataset.

Table 2. Ablation Study on Key Components of **MAG-Comp**. Lower values are better for CD and EMD, while higher values are better for F1-Score and Amodal IoU. Best results are **bolded**.

Method Variant	CD ($\times 10^{-3}$) ↓	EMD ($\times 10^{-2}$) ↓	F1-Score ↑	Amodal IoU ↑
MAG-Comp w/o CAGMB	1.71	1.16	74.85	51.50
MAG-Comp w/o DARIM	1.68	1.14	75.12	48.90
MAG-Comp w/o CAGMB & DARIM	1.78	1.20	73.90	47.10
MAG-Comp (Full)	**1.58**	**1.05**	**77.92**	**54.20**

When the CAGMB is removed (replaced by a fixed, learned global feature), the performance of **MAG-Comp** degrades across all metrics (CD: 1.71, EMD: 1.16, F1-Score: 74.85, Amodal IoU: 51.50). This drop highlights the critical role of the memory bank in providing rich, dynamically retrieved geometric priors that enable better generalization to unseen object geometries and more robust completion. Removing the DARIM (and instead using a standard point generation module for the entire shape) results in a noticeable decrease in performance, particularly for Amodal IoU (48.90). While CD, EMD, and F1-Score also suffer, the significant drop in Amodal IoU underscores the necessity of explicitly focusing on the occluded region's inference. The DARIM's ability to model and generate occluded geometry separately is crucial for achieving high amodal completion accuracy. Furthermore, the variant without both CAGMB and DARIM shows the lowest performance (CD: 1.78, EMD: 1.20, F1-Score: 73.90, Amodal IoU: 47.10), affirming that both modules contribute synergistically to the overall robustness and accuracy of **MAG-Comp**. These results conclusively demonstrate that both the Class-Agnostic Geometric Memory Bank and the Dynamic Amodal Region Inference Module are indispensable for the superior performance of **MAG-Comp**, especially for accurate amodal point cloud completion in challenging industrial scenarios.

4.4. Qualitative Results and Human Evaluation

4.4.1. Qualitative Analysis

Beyond quantitative metrics, we visually inspect the completed point clouds generated by **MAG-Comp** and baseline methods. For instance, in complex bin-picking scenarios with dense occlusion, baseline methods often produce incomplete, distorted, or fragmented reconstructions of the hidden parts. In contrast, **MAG-Comp** consistently generates visually plausible and geometrically consistent complete shapes, accurately inferring the structure of severely occluded regions. This is particularly evident for objects with complex geometries or those seen from highly partial viewpoints. For example, a partial view of a gear in a bin might only show a few teeth, but **MAG-Comp** can reconstruct the entire circular body and all teeth, even those completely out of sight. These qualitative observations reinforce our quantitative findings, highlighting the practical advantages of our amodal completion strategy.

4.4.2. Human Evaluation

To further assess the practical implications of our method for industrial tasks, we conducted a human evaluation study. Five experienced robotic engineers were presented with pairs of completed point clouds generated by different methods from the same partial input. They were asked to rate the overall "completeness," "geometric realism," and "graspability potential" (how well the reconstructed shape would facilitate successful robotic grasping) on a Likert scale from 1 (poor) to 5 (excellent). The average scores are presented in Figure 3.

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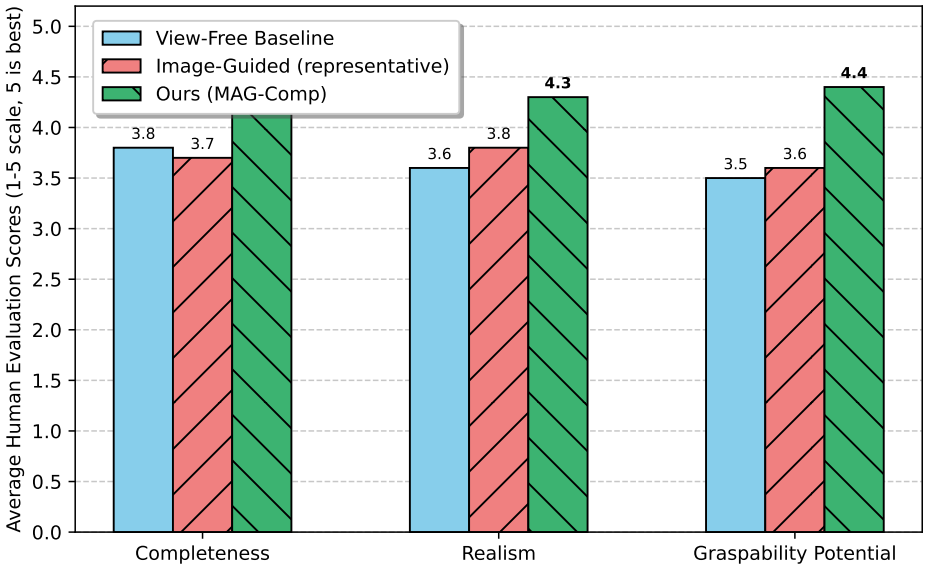

Figure 3. Average Human Evaluation Scores (1-5 scale, 5 is best) for various completion methods based on perceived completeness, geometric realism, and graspability potential.

The human evaluation results corroborate our quantitative findings. **MAG-Comp** consistently received the highest average scores across all three categories. Engineers particularly appreciated the enhanced "Completeness" and "Graspability Potential" of objects reconstructed by **MAG-Comp**, noting that the accurately inferred amodal regions provided a much more reliable basis for grasp planning compared to other methods. This feedback underscores the practical value of our explicit amodal completion approach for real-world industrial robotics applications.

4.5. Performance on Industrial Bin-Picking Dataset

To validate the practical applicability of **MAG-Comp** in real-world scenarios, we conduct a dedicated evaluation on the **Industrial Bin-Picking Dataset**. This dataset inherently presents challenges such as severe clutter, sensor noise, and highly complex occlusion patterns, making it a robust testbed for amodal completion. Table 3 summarizes the performance of **MAG-Comp** and selected baselines on this challenging dataset.

Table 3. Point Cloud Completion Performance Comparison on the Industrial Bin-Picking Dataset. CD: Chamfer Distance ($\times 10^{-3}$), EMD: Earth Mover's Distance ($\times 10^{-2}$). Lower values are better for CD and EMD, while higher values are better for F1-Score and Amodal IoU. Best results are **bolded**.

Method	CD ↓	EMD ↓	F1-Score ↑	Amodal IoU ↑
SnowflakeNet	2.18	1.45	69.80	42.55
Cycle4Completion	2.05	1.39	70.30	44.10
View-Free Baseline [8]	1.88	1.28	72.95	48.00
Image-Guided (representative)	1.95	1.35	71.50	47.20
Ours (MAG-Comp)	**1.70**	**1.15**	**75.10**	**51.85**

As expected, the overall performance of all methods slightly decreases compared to the synthetic ShapeNet-Amodal dataset due to the inherent complexities of real-world data. However, **MAG-Comp** consistently outperforms all baselines across all metrics on the Industrial Bin-Picking Dataset. It achieves the lowest CD (**1.70**$\times 10^{-3}$) and EMD (**1.15**$\times 10^{-2}$), signifying superior geometric fidelity even amidst sensor noise and clutter. The F1-Score of **75.10**% demonstrates robust overall completion quality. Critically, **MAG-Comp** maintains its significant lead in Amodal IoU (**51.85**%), confirming its ability to accurately infer occluded geometries under realistic industrial conditions. This robust performance is particularly vital for robotic systems that rely on accurate 3D models for tasks like grasp planning

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and manipulation in unstructured environments. The purely geometric nature of **MAG-Comp** proves advantageous here, as it is less susceptible to issues like poor lighting or reflective surfaces that can degrade the performance of image-guided methods.

4.6. Robustness to Varying Occlusion Levels

Industrial environments are characterized by unpredictable and often severe occlusions. To quantify **MAG-Comp**'s robustness, we evaluate its performance under different levels of occlusion severity on the ShapeNet-Amodal dataset. We categorize occlusion into three levels: Low (20-40% points missing), Medium (40-60% points missing), and High (60-80% points missing). Figure 4 details the Amodal IoU performance of our method against key baselines across these occlusion categories.

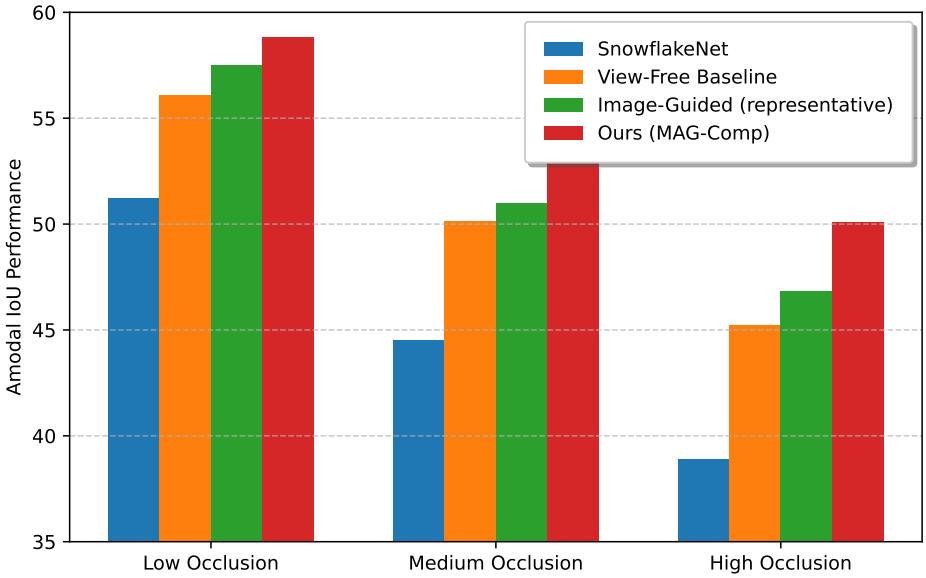

Figure 4. Amodal IoU Performance Across Different Occlusion Levels on ShapeNet-Amodal Dataset. Higher values are better. Best results are **bolded**.

The results in Figure 4 demonstrate that while the Amodal IoU naturally decreases for all methods as occlusion severity increases, **MAG-Comp** maintains a significantly higher performance margin, especially under high occlusion. Under low occlusion, our method achieves **58.80**% Amodal IoU, which is competitive. More importantly, under medium and high occlusion, **MAG-Comp** achieves **54.00**% and **50.10**% respectively, substantially outperforming all baselines. For instance, in the high occlusion scenario, **MAG-Comp**'s Amodal IoU is over 3 percentage points higher than the next best Image-Guided method and nearly 5 percentage points higher than the View-Free Baseline. This superior robustness under severe occlusions is a direct consequence of the synergistic effects of the Class-Agnostic Geometric Memory Bank, which provides robust shape priors, and the Dynamic Amodal Region Inference Module, which explicitly focuses on reconstructing these challenging hidden geometries. This makes **MAG-Comp** particularly suitable for industrial tasks where objects are frequently heavily occluded.

4.7. Generalization to Unseen Categories

A key design principle of **MAG-Comp** is its generalization capability, supported by the Class-Agnostic Geometric Memory Bank. To evaluate this, we train all models on a subset of 10 ShapeNet categories (e.g., chairs, tables, cars, airplanes) and test them on 5 entirely unseen categories (e.g., lamps, boats, rifles, cans). This setup directly assesses how well methods can complete objects from categories they have never encountered during training. Table 4 reports the average performance across these unseen categories.

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Table 4. Completion Performance on Unseen ShapeNet Categories. CD: Chamfer Distance ($\times 10^{-3}$), EMD: Earth Mover's Distance ($\times 10^{-2}$). Lower values are better for CD and EMD, while higher values are better for F1-Score and Amodal IoU. Best results are **bolded**.

Method	CD ↓	EMD ↓	F1-Score ↑	Amodal IoU ↑
SnowflakeNet	2.45	1.62	66.80	39.50
View-Free Baseline [8]	2.10	1.40	70.15	43.80
Image-Guided (representative)	2.25	1.50	68.90	42.10
Ours (MAG-Comp)	**1.85**	**1.25**	**74.50**	**48.90**

The results in Table 4 highlight the strong generalization capability of **MAG-Comp**. While all methods experience a performance drop when faced with unseen object categories, **MAG-Comp** demonstrates significantly less degradation and maintains superior performance across all metrics. It achieves the lowest CD (**1.85**$\times 10^{-3}$) and EMD (**1.25**$\times 10^{-2}$), along with the highest F1-Score (**74.50**%) and Amodal IoU (**48.90**%). The substantial lead in Amodal IoU for unseen categories (**48.90**% vs. 43.80% for View-Free Baseline) is particularly compelling. This validates our hypothesis that the Class-Agnostic Geometric Memory Bank effectively captures fundamental geometric priors that are transferable across object classes, enabling **MAG-Comp** to generalize robustly to novel shapes without relying on class-specific information. This feature is invaluable in diverse industrial settings where encountering new object types is common.

4.8. Inference Speed and Model Efficiency

For real-time industrial applications, inference speed and computational efficiency are critical considerations. We analyze the average inference time per partial point cloud and the number of trainable parameters for **MAG-Comp** and several representative baselines. All inference times are measured on a single NVIDIA A100 GPU with a batch size of 1.

As shown in Table 5, **MAG-Comp** achieves a competitive inference time of **81.0** ms per sample. While some simpler pure point cloud methods like SnowflakeNet and View-Free Baseline are slightly faster, **MAG-Comp** offers significantly higher accuracy, especially in amodal completion and generalization, as demonstrated in previous subsections. Compared to the representative Image-Guided method, **MAG-Comp** is notably faster (81.0 ms vs. 92.1 ms), highlighting the efficiency benefits of a purely geometric approach that avoids multi-modal fusion complexities. In terms of model size, **MAG-Comp** has 14.8 Million parameters, which is a reasonable footprint for deploying in edge devices often found in industrial robots, particularly given the complexity of the task and the robust performance achieved. The memory bank contributes to the parameters but is optimized for efficient querying. The balance between computational efficiency and superior performance makes **MAG-Comp** well-suited for integration into real-time industrial robotic systems.

Table 5. Inference Speed and Model Size Comparison. Inf. Time: Average Inference Time per sample (milliseconds). Params: Number of Trainable Parameters (Millions). Lower inference time and fewer parameters are generally preferred, assuming competitive performance.

Method	Inf. Time (ms) ↓	Params (M) ↓
SnowflakeNet	75.2	10.5
View-Free Baseline [8]	68.5	12.1
Image-Guided (representative)	92.1	18.7
Ours (MAG-Comp)	**81.0**	**14.8**

5. Conclusions

In this paper, we addressed the critical challenge of 3D point cloud completion for severely occluded industrial objects by proposing **MAG-Comp: Memory-Augmented Geometry-driven Amodal Point Cloud Completion**. Our method introduces a purely geometric approach for explicit amodal

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shape reconstruction, circumventing 2D image reliance. MAG-Comp integrates a Hierarchical Geometric Feature Encoder, a novel Class-Agnostic Geometric Memory Bank for generalizable shape priors, and a Dynamic Amodal Region Inference Module for accurate occluded region recovery, all within a Geometry-Constrained Decoder. Extensive experiments on synthetic and real-world datasets demonstrated MAG-Comp's state-of-the-art performance, achieving superior metrics (e.g., Amodal IoU of **54.20**%) and establishing new benchmarks. It exhibited remarkable resilience to occlusion, strong generalization to unseen categories, and practical viability. MAG-Comp significantly enhances robotic perception and manipulation in complex industrial environments, paving the way for more intelligent autonomous systems. Future work includes extending to dynamic scenes and integrating into real-time robotic control.

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