ICRA2026 Late Breaking Results Poster presented at
2026 IEEE International Conference on Robotics and Automation (ICRA 2026)
June 1-5, 2026. Vienna, Austria

Gaussian Splatting and Point Cloud-Based Workspace Prediction for Collision-Free Trajectory Planning in Collaborative Robots

Jungho Seo[1], Dongwook Kim[1]*
[1]Department of Robotics and Mechatronics Engineering, DGIST
sjh1436@naver.com, dw_kim@dgist.ac.kr
*Corresponding author

***Abstract*—As multi-robot collaboration becomes increasingly prevalent in modern industrial settings, ensuring collision-free operation among robots sharing the same workspace remains a critical challenge. This paper proposes an integrated framework that combines 3D Gaussian Splatting (3D-GS) for high-fidelity scene reconstruction, Generalized Iterative Closest Point (GICP) with Fast Global Registration (FGR) for robust pose estimation, a Deep Graph Convolutional Neural Network (DGCNN) for joint angle regression from point cloud data, Dynamic Mode Decomposition (DMD) for trajectory prediction, and a Control Barrier Function (CBF) for real-time safety enforcement. Through experiments, we validated the trajectory prediction of 0-DOF objects and confirmed that joint angle prediction is feasible from 3D-GS-based PLY data using DGCNN-based regression, with training data collected at joint angle intervals of $15°$–$45°$.**

***Index Terms*—3D Gaussian Splatting, Collaborative Robots, Trajectory Prediction, DGCNN, Control Barrier Function, GICP**

I. INTRODUCTION

Modern manufacturing environments demand robotic systems capable of operating collaboratively while avoiding workspace interference and collisions. Traditional industrial robots execute fixed, pre-programmed trajectories and lack the situational awareness required to respond to the dynamic motion of neighboring robots.

Although vision-language models (VLMs) offer flexible reasoning capabilities, they impose substantial computational overhead and require continuous monitoring of the entire environment, making real-time deployment in constrained industrial settings impractical [1].

To address these limitations, we propose a predictive, safety-guaranteed trajectory optimization framework built upon lightweight and explicit 3D scene representations, designed to remain robust even in “non-visible” situations where visual data is partially occluded.

II. METHODOLOGY

A. 3D Scene Reconstruction via Gaussian Splatting

The framework begins with 3D Gaussian Splatting (3D-GS) [2], which reconstructs the robot’s operational environment from multi-view images as an explicit set of 3D Gaussian primitives. Each Gaussian encodes its mean position $\boldsymbol{\mu} \in \mathbb{R}^3$, covariance matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{3\times 3}$, opacity σ, and spherical harmonic coefficients for view-dependent colour. The representation supports real-time rendering and straightforward conversion into point cloud (PLY) format for downstream processing.

B. Pose Estimation: GICP-FGR Pipeline

Raw point clouds extracted from successive 3D-GS reconstructions are registered using a two-stage pipeline. Fast Global Registration (FGR) computes a coarse initial alignment, reducing sensitivity to poor initializations. Generalized ICP (GICP) then refines the result by incorporating per-point covariance matrices, improving robustness against surface singularities. The GICP cost function is

$$\mathbf{T}^* = \arg\min_{\mathbf{T}} \sum_i \mathbf{d}_i^\top \left(\mathbf{B}_i + \mathbf{T}\mathbf{A}_i\mathbf{T}^\top\right)^{-1} \mathbf{d}_i, \qquad (1)$$

where $\mathbf{d}_i = \mathbf{b}_i - \mathbf{T}\mathbf{a}_i$ is the point residual and $\mathbf{A}_i$, $\mathbf{B}_i$ are per-point covariance matrices of the source and target clouds. The resulting rigid transformation $\mathbf{T} = [\mathbf{R} \mid \mathbf{t}]$, with $\mathbf{R} \in SO(3)$ and $\mathbf{t} \in \mathbb{R}^3$, encodes the 6-DoF pose change of the collaborative robot.

C. Joint Angle Regression via DGCNN

A Dynamic Graph Convolutional Neural Network (DGCNN) infers the angular configuration of each manipulator joint directly from point cloud geometry. The model constructs a k-nearest-neighbour graph over input points and applies EdgeConv operations at each layer:

$$\mathbf{h}_i^{(\ell+1)} = \max_{j\in\mathcal{N}(i)} h_\Theta\left(\mathbf{h}_i^{(\ell)},\, \mathbf{h}_j^{(\ell)} - \mathbf{h}_i^{(\ell)}\right), \qquad (2)$$

where $\mathbf{h}_i^{(\ell)}$ is the feature of point i at layer ℓ, $\mathcal{N}(i)$ denotes its k nearest neighbours, and h_Θ is a shared MLP. A dataset of 125 samples collected at joint angle intervals of $15°$–$45°$ was expanded to 3,750 training samples via geometric data augmentation (rotation and translation perturbations of PLY files).

D. Trajectory Prediction via DMD

Given a temporal sequence of GICP-derived poses $\{(\mathbf{R}_i, \mathbf{t}_i)\}_{i=1}^{N}$, the Koopman-based Dynamic Mode Decomposition (DMD) model identifies a linear operator $\mathbf{A}$ in a lifted feature space:

$$\boldsymbol{\psi}(\mathbf{x}_{k+1}) \approx \mathbf{A}\,\boldsymbol{\psi}(\mathbf{x}_k), \qquad \mathbf{A} = \mathbf{\Psi}'\mathbf{\Psi}^{\dagger}, \tag{3}$$

where $\boldsymbol{\psi} : \mathbb{R}^n \to \mathbb{R}^p$ is an observable lifting map, $\mathbf{\Psi}$ and $\mathbf{\Psi}'$ are data matrices of consecutive snapshots, and $(\cdot)^{\dagger}$ denotes the Moore–Penrose pseudoinverse. The model predicts the next pose from as few as two or three prior observations.

E. Safety Enforcement via Control Barrier Function

The predicted workspace of the collaborative robot defines the safety set

$$\mathcal{C} = \left\{ \mathbf{x} \in \mathbb{R}^n \;\middle|\; h(\mathbf{x}) \geq 0 \right\}, \tag{4}$$

where $h(\mathbf{x})$ is a smooth barrier function encoding the minimum allowable distance between robot bodies. A CBF-based Quadratic Program (QP) filters the nominal control input $\mathbf{u}_0$ in real time:

$$\mathbf{u}^* = \arg\min_{\mathbf{u}} \ \|\mathbf{u} - \mathbf{u}_0\|^2 \quad \text{s.t.} \quad \dot{h}(\mathbf{x}, \mathbf{u}) + \alpha(h(\mathbf{x})) \geq 0, \tag{5}$$

which forward-invariantly maintains the system within $\mathcal{C}$ [3], [4].

III. EXPERIMENTAL RESULTS

A. GICP-FGR Registration

Initial experiments with Point-to-Point ICP revealed two fundamental failure modes: (1) *point singularity alignment*, in which degenerate planar or edge-dominant regions caused ill-conditioned optimisation; and (2) *Euler angle redundancy*, in which gimbal-lock-like ambiguities led to unstable rotation estimates. Replacing Point-to-Point ICP with Point-to-Plane ICP resolved the singularity issue by constraining correspondences to local tangent planes. Further adoption of GICP (1) improved matching accuracy through per-point covariance weighting, while FGR preprocessing substantially reduced initial alignment computation time. The GICP-FGR pipeline yielded stable rotation and translation estimates for rigid objects across all tested configurations.

B. Trajectory Prediction via DMD

The DMD model was evaluated on a synthetic nonlinear test sequence arranged along a 3D quadratic-like trajectory in Cartesian space. Given the last observed position $\mathbf{t} = [60.0,\ 60.0,\ 14.954]^{\top}$ and its preceding context, the model predicted

$$\hat{\mathbf{t}}_{N+1} = \left[62.0,\ 62.0,\ 14.234\right]^{\top}. \tag{6}$$

The predicted rotation matrix satisfied $\hat{\mathbf{R}}^{\top}\hat{\mathbf{R}} = \mathbf{I}$ and $\det(\hat{\mathbf{R}}) = 1$, confirming physically valid $SO(3)$ membership without explicit constraint enforcement.

C. Joint Angle Regression via DGCNN

Results are summarised in Table I. After training on 3,750 augmented PLY samples, the test MAE decreased significantly for all evaluated joints. Scatter-plot analysis confirmed that predicted values clustered near the perfect-prediction diagonal, validating the feasibility of DGCNN-based joint angle estimation from 3D-GS PLY data.

TABLE I
JOINT ANGLE REGRESSION MAE BEFORE AND AFTER TRAINING

Metric	**Joint 1**	**Joint 2**	**Joint 4**
Initial MAE	10.76°	22.28°	40.05°
Final MAE	**5.10°**	**12.21°**	**18.95°**
Improvement	52.6 %	45.2 %	52.7 %

IV. CONCLUSION AND FUTURE WORK

This paper presented an integrated framework for workspace prediction and collision-free trajectory planning in collaborative robot environments. The GICP-FGR pipeline successfully resolved singularity and Euler angle redundancy issues inherent in standard ICP, yielding stable 6-DoF pose estimates. The DMD model demonstrated the ability to predict physically consistent future poses (6) from sparse observations, while the DGCNN achieved meaningful joint angle regression accuracy with augmented 3D-GS point cloud data.

Nevertheless, scatter-plot results reveal a persistent limitation: the variance of predicted joint angles is broadly distributed across the full angular range, indicating insufficient discrimination among fine-grained angular configurations. Three directions are identified for future work:

1) *Geometric data augmentation:* Additional 3D rotation and translation perturbations applied directly to PLY files will increase training-data diversity and improve model generalisation.
2) *Fine-grained angular sampling:* The current coarse sampling (15°–45° intervals) will be refined to denser steps, enabling learning of a more continuous joint angle distribution.
3) *Classification-then-Regression:* A per-joint angle-range classifier will be prepended to the regression stage, constraining the search space and thereby reducing MAE.

REFERENCES

[1] S. Hu *et al.*, "VLSA: Vision-language-action models with plug-and-play safety constraint layer," *arXiv preprint arXiv:2512.11891*, 2025.

[2] J. Zeng *et al.*, "Multi-robot autonomous 3D reconstruction using Gaussian splatting with semantic guidance," *IEEE Robot. Autom. Lett.*, 2025.

[3] J. Huang *et al.*, "Dynamic collision avoidance using velocity obstacle-based control barrier functions," *IEEE Trans. Control Syst. Technol.*, 2025.

[4] J. Park *et al.*, "A ship collision avoidance algorithm using control barrier functions based on velocity obstacles with consideration of COLREGs," *J. Inst. Control Robot. Syst.*, vol. 31, no. 11, pp. 1271–1276, 2025.