MvFFN: Multi-view Floor plan Feed-Forward Network for Unposed Wide-Baseline Panorama Layout Reconstruction

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Abstract

Reconstructing accurate camera poses and floor plan layouts from sparse, unposed, wide-baseline RGB panoramas remains a challenging open problem. Direct multi-room floor plan prediction is especially difficult in this setting: pose, geometry, semantics, and global layout structure are tightly coupled, yet a complete floor plan is hard to learn as a single global output. We address this challenge with *Multi-view Ordered Wall Instance Segmentation* (*MOIS*), a new formulation that replaces direct global wall-sequence prediction with local cross-view wall instances and within-room wall connectivity. Building on this formulation, we propose *MvFFN*, a feed-forward multi-view transformer that jointly predicts coarse camera poses, dense global geometry, and wall-instance-level semantic outputs with globally consistent identities and within-room connectivity. A downstream *Layout Chaining* (*LC*) post-processing pipeline then assembles these predictions into multi-room floor plans with shared global coordinates, consistent wall identities, and connected room structure. The resulting pipeline substantially outperforms prior methods on wall- and junction-level accuracy. Moreover, the predicted wall instances enable fully automatic downstream layout refinement, with planar bundle adjustment improving a majority of scenes and yielding clear gains on the subset that benefits. We also introduce `ZInD-CrossView`, a re-annotated dataset with globally unique wall instances and cross-view segmentation labels for this task. Visit the project website at: https://yuguang-li.github.io/mvffn.

1 Introduction

Reconstructing floor plan layouts and camera poses from panoramic images is important for applications such as augmented reality, indoor digital twins, immersive walkthrough generation, and autonomous navigation. Recovering complete multi-room layouts requires multiple views because of occlusions and limited visibility. However, existing methods typically avoid the setting of unposed, wide-baseline panoramas: they assume known camera poses Yue et al. [2023], Avetisyan et al. [2024], Liu et al. [2024], require small-baseline captures Avetisyan et al. [2024], or rely on human-in-the-loop adjustment Cruz et al. [2021], Li et al. [2025]. A fully automatic approach for reconstructing layouts and poses from unposed, wide-baseline panoramas would substantially reduce capture and annotation effort and enable broader deployment at scale.

A floor plan encodes wall geometry, local connectivity, and room-level organization. Recovering it from multiple views requires associating wall instances across views, inferring their connectivity despite occlusion, and separating structures that belong to different rooms. Geometry alone is often insufficient. When camera poses are unknown and fused point maps are noisy, reconstruction often

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suffers from duplicate walls, missing walls, and incorrect junctions, which reduce both wall and junction-level precision and recall. In contrast, images provide critical semantic cues for grouping pixels across views by wall instance, inferring local connectivity, and resolving room assignments. At the same time, directly predicting a complete multi-room floor plan as a single global output is difficult to learn. Large multi-room layouts often contain ambiguous room partitions, limited observations can obscure small structural details, and small local sequence errors can cascade into large global drift. The problem is further compounded by the scarcity of datasets that provide structured multi-room layouts together with camera-registered multi-view panoramas. This motivates the central insight of our paper: rather than predicting a global floor plan directly, we recast multi-view, multi-room layout estimation around local wall relations that are easier to supervise and more robust to noisy annotations.

To this end, we study structured floor plan and camera-pose reconstruction from sparse, unposed 360° panoramas, producing complete layouts when view coverage is sufficient and partial layouts under occlusion. We formalize this idea as *Multi-view Ordered Wall Instance Segmentation* (*MOIS*), which replaces direct global floor plan prediction with local wall instances and within-room wall connectivity that remain consistent across views. Based on *MOIS*, we propose *MvFFN*, a feed-forward multi-view network that predicts pixel-grounded wall instances and their within-room connectivity from cross-view geometric and semantic cues, and a *Layout Chaining* (*LC*) post-processing pipeline that assembles these local predictions into multi-room floor plans with consistent wall identities in a shared global frame. *MvFFN* also predicts coarse camera poses and dense global geometry, while the inferred wall instances enable downstream layout bundle adjustment for further refinement. Together, these design choices make multi-view layout estimation more learnable under scarce data and noisy supervision. Accordingly, the learned contribution is *MOIS*/*MvFFN*, while global assembly remains deterministic and the geometric priors address current data scarcity; Appendix I details these limitations and future directions.

The contributions of this work are as follows: (1) We introduce *MOIS*, a new formulation for multi-view, multi-room layout estimation based on local cross-view wall instances and within-room wall connectivity. (2) We introduce *MvFFN*, a feed-forward multi-view network that predicts these local wall structures from cross-view geometric and semantic cues. We show gains both before and after layout assembly: dense *MOIS* predictions improve raw cross-view wall-slot quality, while the assembled global layouts substantially improve wall and junction accuracy over prior modular baselines across both 5-view and 8-view settings. (3) We introduce `ZInD-CrossView` (`ZInD-XV`) dataset with globally unique wall instances and cross-view segmentation annotations.

2 Related Work

Layout estimation. Most layout estimation methods combine a dense geometric front-end with a back-end that vectorizes predictions into wall and corner instances and room topology Sun et al. [2021a]. In the single-view setting, methods predict monocular 1D floor boundaries Yang et al. [2019], Wang et al. [2021], Jiang et al. [2022], Sun et al. [2021b], Shen et al. [2023], Tsai et al. [2024] and recover wall and corner sequences through post-processing Zou et al. [2018], Sun et al. [2019], Pintore et al. [2020], relying on the clockwise image-column order within a single panorama. This cue does not directly extend to sparse multi-view settings, where each view observes only a partial layout under occlusion. For multi-room floor-plan estimation, most methods instead assume accurate camera poses and dense point clouds, and infer structure mainly from fused geometric cues in top-down space. *Plane-DUSt3R* Huang et al. [2025] predicts structural-plane point maps and recovers wall instances and topology through post-processing. Under imperfect geometry, connectivity is typically recovered with heuristic optimization Chen et al. [2019], Wang et al. [2022], Hanning et al. [2025] or learned polygon and graph decoders Liu et al. [2024], Yue et al. [2023], Chen et al. [2023], Su et al. [2023], Pintore et al. [2025]. By contrast, cross-view semantic cues remain underused for resolving wall identity and connectivity under pose uncertainty. *SceneScript* Avetisyan et al. [2024] shows that, given camera poses and RGB video, semantic context can improve structured layout estimation.

Wide-baseline pose and geometry estimation. Wide-baseline indoor pose estimation remains difficult for traditional *Structure-from-Motion* Schonberger and Frahm [2016], Moulon et al. [2016], Lambert et al. [2022]. Recent learning-based models improve dense 3D geometry and camera pose estimation from wide-baseline inputs Wang et al. [2024, 2025], Tang et al. [2025], Jung et al. [2025]. For indoor 360° panoramas, limited training data often constrains geometry estimation

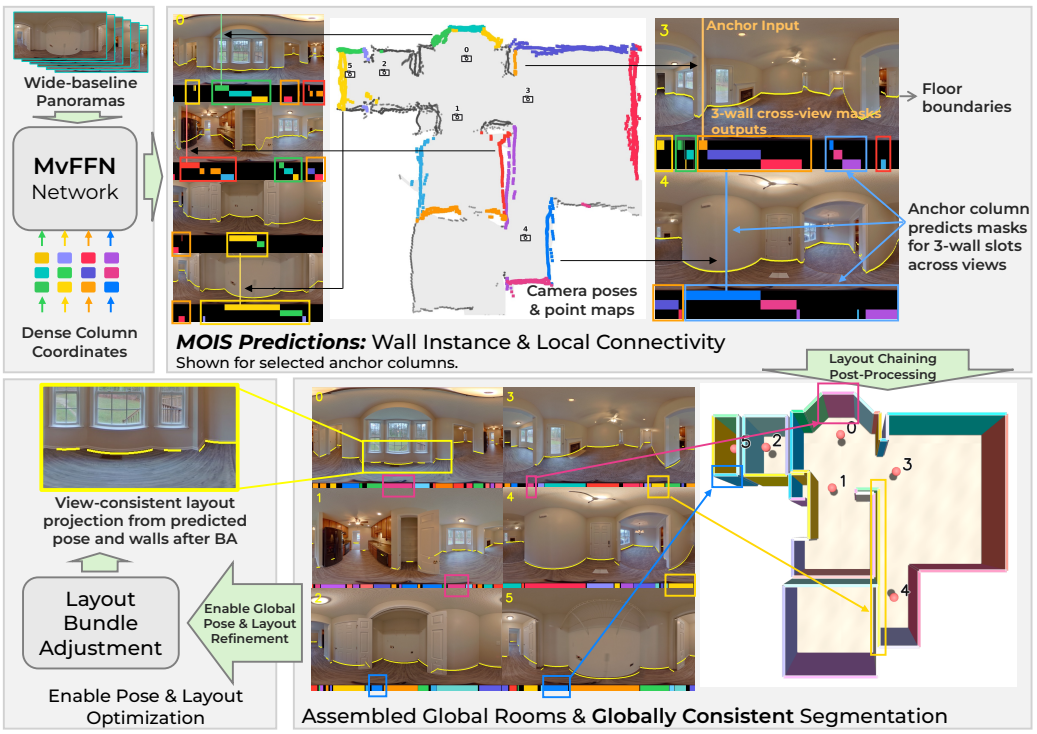

Figure 1: *MvFFN* reformulates floor plan reconstruction from direct global prediction to local *MOIS* prediction: each anchor column, shown as a vertical line in the panorama, predicts cross-view masks for the anchor wall and two clockwise adjacent walls. Colors indicate corresponding wall slots/instances across panoramas and in the assembled layout. *Layout Chaining* aggregates these local predictions into global wall identities, room-level wall sequences, and metric floor plan layouts, enabling downstream refinement.

to 1D floor boundary representations rather than dense per-pixel 3D geometry Hutchcroft et al. [2022], Tu et al. [2024], Nejatishahidin et al. [2023]. *BADGR* Li et al. [2025] shows that semantic layout correspondences and geometry are complementary: once pixel-to-wall correspondences and initial estimates are available from unposed wide-baseline images, poses and layouts can be jointly optimized to reduce initial errors.

3 Overview

Large multi-room floor plans often contain ambiguous room boundaries, occluded wall connectivity, and distant structural details, making direct floor-level sequence prediction brittle to error accumulation. We therefore reconstruct layouts through dense local *MOIS* predictions rather than direct global floor plan prediction.

Our bottom-up pipeline (Figure 1) takes N panoramas and evaluates *MvFFN* densely at every column of every view. Each anchor column defines one *MOIS* target: the cross-view assignments of the current wall and its within-room neighbors. Aggregating all anchors yields dense anchor-conditioned *MOIS* assignments over multiple views, predicted jointly with global geometry under pose uncertainty.

MvFFN uses a multi-view geometric encoder, trained from scratch and inspired by *VGGT* Wang et al. [2025], adapted to panoramic 2D column tokens and dense column-wise outputs. A floor-layout semantic branch combines image and geometric features for local wall-instance reasoning. We describe the geometric encoder and floor-layout decoder in Sec. 4.1 and Sec. 4.2, respectively.

Finally, the dense local *MOIS* predictions are assembled into global room layouts via *Layout Chaining* (Sec. 4.5). The predicted pixel-to-wall correspondences and initial layouts can also support downstream layout refinement, which we evaluate with layout bundle adjustment in Sec. 4.6.

4 Method

We formulate multi-room layout reconstruction from sparse panoramas Zhang et al. [2014] as the recovery of global 3-DoF camera poses (2D position and 1D rotation), structured 2D floor layouts, and a local anchor-conditioned wall representation across views.

Inputs. We assume a set of N straightened 360° RGB panoramas $\{I_i\}_{i=1}^N$ Zhang et al. [2014], where each $I_i \in \mathbb{R}^{3\times H\times W}$ is given in equirectangular projection. The panoramas are sparsely captured in an indoor environment and are assumed to form a single pose graph whose neighboring views have at least 20% co-visibility similar to Cruz et al. [2021], Hutchcroft et al. [2022], Li et al. [2025]. We further assume that relative camera heights are known across the floor.

***MvFFN* outputs.** For each panorama I_i, *MvFFN* predicts four intermediate quantities: (1) a 3-DoF camera pose $E_i \in SE(2)$; (2) dense per-column floor boundaries $\mathcal{B}_i \in \mathbb{R}^{2\times W}$; (3) dense per-column floor point maps $\mathcal{P}_i \in \mathbb{R}^{4\times W}$ and wall-line parameters $\Lambda_i \in \mathbb{R}^{3\times W}$; and (4) for each anchor column, a dense *MOIS* probability field $\hat{\mathcal{S}}$ over columns across all views, encoding assignments to the underlying global wall instance intersected by the anchor ray and its within-room neighboring wall slots.

***MOIS* formulation.** We formalize the local wall-instance and within-room connectivity predictions described above with *MOIS*, an anchor-conditioned ordered wall representation defined for each image column (see Fig. 1 for intuition). Let $\mathcal{C}_{i,c}$ denote anchor column c in panorama I_i. The anchor ray determines the current room by the first wall it intersects: if it intersects a closed door, the door is assigned to the attached wall instance and the current room remains the attached room; if it passes through an open doorway, the current room is the room containing the first visible wall it intersects. The corresponding *MOIS* target is then a local ordered K-wall tuple

$$\mathbf{w}_{i,c} = \left(w_{i,c}^{(0)}, w_{i,c}^{(1)}, \ldots, w_{i,c}^{(K-1)}\right),$$

where $w_{i,c}^{(0)}$ is the intersected wall instance defining the current room, and $w_{i,c}^{(r)}$ denotes the r-th clockwise physically adjacent wall within that room. We convert this local tuple into a dense binary assignment tensor $\mathcal{S}^{\mathrm{gt}}$, where each entry indicates whether column (j, d) is assigned to a given ordered wall slot of the anchor column. This dense local representation serves as the semantic target for the floor-layout semantic branch in Sec. 4.2 and is assembled into global layouts by *Layout Chaining* in Sec. 4.5.

Final layout outputs. The primary outputs are 3-DoF camera poses $\{E_i\}_{i=1}^N$ and global room layouts $\{\mathcal{W}^m\}$. Unlike the local anchor-conditioned *MOIS* tuples, each $\mathcal{W}^m$ represents the final reconstructed wall geometry of room m in the global floor coordinate frame after *Layout Chaining*. We also maintain an auxiliary column-to-wall map $\mathcal{M} : \mathcal{C}_{i,c} \to w^\ell$, which associates each image column with at most one global wall instance. The room corners $V^m = (v^{m,1}, \ldots, v^{m,K_m})$ are obtained by intersecting consecutive wall segments, where $v^{m,k} \in \mathbb{R}^2$ and K_m is the number of corners. Depending on visibility, a room layout may be closed or remain open under occlusion.

4.1 N-view Geometry Encoder Branch

The geometry branch is a multi-view encoder for dense geometric prediction, including camera pose, floor-boundary depth, and point maps. Architecturally, it is similar to *VGGT* Wang et al. [2025], while operating on panoramic column-wise features. Each panorama I_i is processed by an *EfficientNet-v2* backbone Tan and Le [2021], followed by a Height Compression Module (HCM) Sun et al. [2019] that produces column-patch features $f_i^G \in \mathbb{R}^{S\times C}$, where $S = 256$, $C = 1024$, and each patch spans $4 \times H$ pixels.

Patch encodings. We add angular column embeddings (ACE) and sinusoidal camera positional encodings (CPE) Vaswani [2017] to obtain geometry tokens F^G. The ACE are *Fourier features* Tancik et al. [2020] of per-patch viewing angles. For each column-patch, the viewing angle combines: (1) an intra-frame horizontal angle $\theta_{i,c}^h \in [0^\circ, 360^\circ)$ corresponding to the patch-center azimuth, and (2) a precomputed vanishing angle $\theta_i^v \in [-45^\circ, 45^\circ)$ for camera i Zhang et al. [2014]. Incorporating vanishing-angle embeddings exploits the high precision of indoor vanishing angles Li et al. [2025], Lambert et al. [2022] to axis-align the predicted floor layout. The global floor coordinate frame is centered at the first camera and oriented by its vanishing angle.

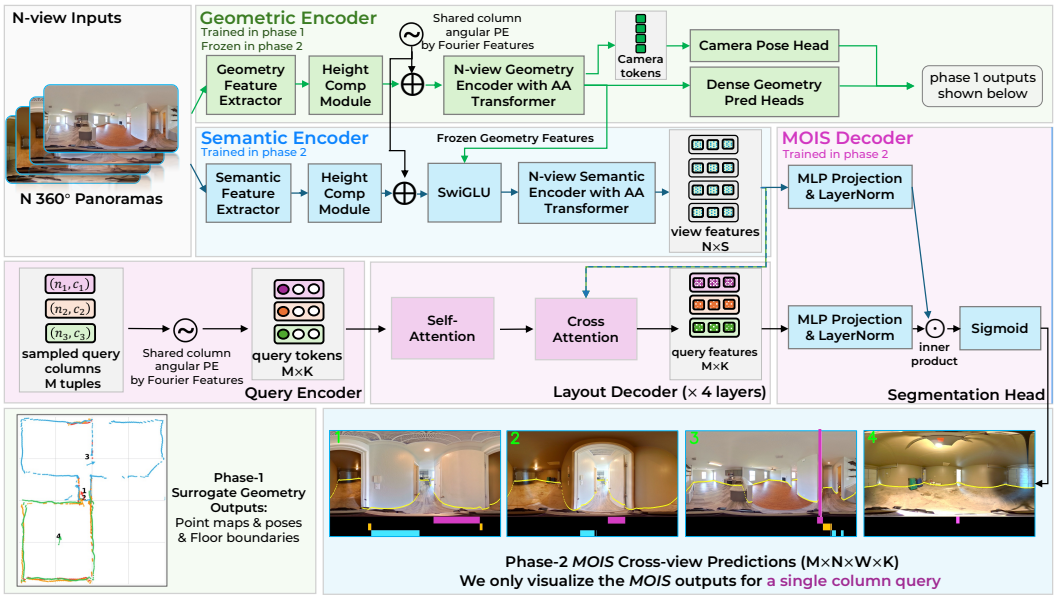

Figure 2: Architecture of *MvFFN* with two-stage training for *MOIS* prediction.

Alternating-attention transformer. We concatenate geometry tokens from all views, $t^G = \bigcup_{i=1}^{N} f_i^G$, with camera tokens $t_i^C \in \mathbb{R}^{1\times C}$ and register tokens $t_i^R \in \mathbb{R}^{4\times C'}$ Darcet et al. [2023], and process them with a 12-layer alternating-attention transformer Wang et al. [2025]. The transformer alternates between frame-wise and global attention layers implemented with *FlashAttention* Dao et al. [2022], and produces updated geometry, camera, and register tokens $(\hat{t}_i^G, \hat{t}_i^C, \hat{t}_i^R)_{i=1}^N$.

Dense predictions. We use separate multi-layer perceptron (MLP) heads to predict dense floor boundaries $\hat{\mathcal{B}}$, 2D floor point maps $\hat{\mathcal{P}}$, and 2D wall-line parameters $\hat{\Lambda}$. The point-map output contains both 2D floor coordinates and their 2D aleatoric uncertainties. Each supporting line is represented by a 2D orientation vector and a bias term. Floor boundaries and point maps are predicted with aleatoric uncertainty Kendall and Cipolla [2016]. Following prior panorama layout work Sun et al. [2019], Hutchcroft et al. [2022], Li et al. [2025], floor boundaries and point maps are supervised using derived column-wise targets that pass through open doorways and ignore occlusions from furniture and other non-structural objects, subject to dataset-specific annotation conventions. Camera poses are predicted from per-camera register and camera tokens Wang et al. [2025] using an MLP head with adaptive LayerNorm Perez et al. [2018].

4.2 Floor Layout Semantic Branch

Our floor-layout semantic branch predicts the dense *MOIS* probability field introduced in Sec. 4. Specifically, for each anchor column, it estimates which columns across all views belong to the current wall and to its next $K-1$ clockwise physically adjacent within-room neighbors. We use $K=3$, which provides enough neighboring-wall context for stable connectivity recovery in *Layout Chaining* (Sec. 4.5), while avoiding the degradation of longer prediction windows (Sec. 6). The branch consists of a semantic N-view encoder conditioned on geometry features, a cross-attention transformer decoder with anchor-conditioned wall-slot queries, and a segmentation head.

Semantic N-view encoder. The semantic encoder follows the geometry branch architecture from Sec. 4.1. Each panorama is processed by an *EfficientNet-v2* backbone and HCM to produce column-patch features $f_i^S \in \mathbb{R}^{S\times C}$. These features are fused with the frozen geometry tokens $\hat{t}_i^G$ through a SwiGLU module, and the fused features are then processed by a four-layer semantic alternating-attention transformer, producing semantic column tokens $\hat{t}_i^S$.

Anchor-conditioned wall-slot queries. We adopt a two-level query design with $M \times K$ learned query tokens, where M is the number of sampled anchor columns and K is the number of ordered *MOIS* wall slots. Each query group corresponds to one anchor column and contains K ordered

query tokens associated with the wall slots $r \in \{0, \ldots, K-1\}$. Given sampled anchor columns $\{(i_m, c_m)\}_{m=1}^{M}$, we initialize query-group features using the angular encoding of the anchor column together with a camera identity encoding.

Transformer decoder. The decoder has four stacked layers. Within each anchor group m, self-attention operates over the K ordered wall-slot queries, and cross-attention is applied to the semantic column tokens from all views. The decoder outputs updated query features $\hat{t}^q_{m,r}$, one for each anchor m and wall slot r.

***MOIS* probability prediction.** Let $\tilde{t}^q_{m,r} \in \mathbb{R}^{C'}$ and $\tilde{t}^I_{j,d} \in \mathbb{R}^{C'}$ denote the projected query and semantic features for anchor-slot (m, r) and column (j, d), respectively. We compute the dense *MOIS* probability field as

$$\hat{\mathcal{S}}_{m,j,d,r} = \sigma\big(\langle \tilde{t}^q_{m,r}, \tilde{t}^I_{j,d} \rangle\big)\,, \tag{1}$$

where $\hat{\mathcal{S}}_{m,j,d,r}$ is the probability that column (j, d) belongs to the r-th ordered wall slot of anchor m. During training, M anchor columns are randomly sampled subject to GPU memory limits. During inference, we set $M = NW$ and predict the dense *MOIS* field for all anchor columns in all views in a single forward pass; equivalently a 5D tensor indexed by view and anchor column, as in Algorithm 1.

4.3 Training

We train *MvFFN* in two stages because the geometry and semantic objectives compete under joint training. In the first stage, we train the geometry branch for dense geometric prediction, including floor boundaries, floor point maps, and camera poses, using a multi-task objective that combines geometric supervision with absolute and relative pose losses. In the second stage, we freeze the pre-trained geometry branch and train the floor-layout semantic branch from scratch under dense *MOIS* supervision, reusing the geometry features from stage one. The *MOIS* objective is factorized into a wall-presence term, which predicts whether a column belongs to any ordered wall slot of the anchor, and an ordered wall-slot classification term applied to positive assignments. In both stages, training samples are formed by drawing sparse multi-view panorama groups from a single pose graph with sufficient co-visibility. Full loss definitions, optimizer settings, and sampling schedules are provided in Appendix A.

4.4 Inductive Bias for Training Data Scarcity

Training sparse multi-view models is substantially harder than training 2-view models because they require more diverse multi-view samples, while the number of scenes and unique structured training examples remains limited. In our settings, this makes naive 3-view to 5-view training unstable even when the same data is sufficient for strong 2-view geometric learning. This trend is also consistent with recent geometric models such as *VGGT* Wang et al. [2025] and *MV-DUSt3R* Tang et al. [2025], which require substantially more training data than *DUSt3R* Wang et al. [2024] to improve 2-view pose accuracy. To improve convergence under this regime, we introduce two inductive biases based on reliable 2-view *CovisPose* Hutchcroft et al. [2022] predictions.

Camera rotation priors. Two-view geometric models already provide reliable camera rotations, and per-panorama vanishing points further improve indoor rotation accuracy Zhang et al. [2014], Lambert et al. [2022]. We first run the 2-view *CovisPose* model and recover global camera rotations with a minimum spanning tree, following *BADGR*'s initialization strategy Li et al. [2025]. These refined rotations are then injected as conditioning signals into the angular encoder (Sec. 4.1). This reduces the amount of scarce multi-view supervision spent on relearning camera rotation and lets the model focus on the harder cross-view geometric reasoning problem, while retaining near 2-view rotation accuracy without requiring substantially more N-view training data.

Column-patch correspondence priors. Under limited multi-view training data, we use precomputed 2-view *CovisPose* correspondences during both training and inference to restrict early cross-view attention to a local window around predicted matches, rather than relearning global correspondence search from scratch. We implement this by masking the first four global self-attention layers of the alternating-attention transformer: for each column-patch token in view I_a, tokens in view I_b more than 40 columns away from the predicted match are masked out, and fully non-covisible view pairs

are blocked entirely. This reduces correspondence ambiguity, leading to less noisy gradients and faster convergence.

4.5 Layout Chaining

Layout Chaining (*LC*) is a deterministic procedure that reduces dense local *MOIS* predictions into global column-to-wall assignments $\mathcal{M}$, room-level wall sequences $\{\mathcal{L}^m\}$, and room endpoints $\{V^m\}$. Since many anchor columns provide overlapping same-wall and neighboring-wall evidence, *LC* first consolidates wall identity and then recovers within-room adjacency. It clusters same-view current-wall predictions $\hat{\mathcal{S}}[n, :, n, :, 0]$ into per-view wall instances L_n, then merges these across views into global wall groups through a cross-view same-wall graph. Directed within-room adjacency is estimated from the neighboring *MOIS* slots, producing a room graph whose edges are filtered by geometric consistency and whose longest directed paths define partial room layouts $\mathcal{L}^m$. Finally, wall-line parameters are fit from supporting point-map predictions grouped by $\mathcal{M}$, and room endpoints are recovered by intersecting consecutive walls. Algorithm details are provided in Appendix B.

4.6 Layout Bundle Adjustment

Planar bundle adjustment (*BA*) and *BADGR* Li et al. [2025] are not contributions of this work; we evaluate them to show that *MvFFN*'s automatic correspondences make fully automatic downstream refinement from unposed panoramas possible for the first time. The layouts produced by *Layout Chaining* and the predicted camera poses may still violate multi-view consistency and structural layout constraints. The predicted pixel-to-wall correspondences provide the associations needed for refinement. We investigate whether these methods can use the correspondences to improve poses and wall geometry. Sec. 5.3 reports the results.

5 Experiments

We evaluate primarily on `ZInD-XV`, which extends `ZInD` Cruz et al. [2021] with globally indexed multi-room layouts represented as room-wise wall sequences, and per-panorama column-wise floor-boundary and wall-instance labels derived from those layouts. `ZInD-XV` contains 2,706 floors and 66,834 panoramas. We additionally use `HM3D-XV`, a smaller auxiliary benchmark derived from residential `HM3DSem` scenes Yadav et al. [2023], with 372 floors and 17,943 panoramas, to evaluate cross-dataset transfer to furnished, mesh-rendered indoor scenes. Dataset construction and annotation details are provided in the supplementary material.

We compare against modular baselines assembled from existing pose, geometry, and layout components. The main evaluation measures final structured floor-layout accuracy after *Layout Chaining*; we also report pose estimation and downstream refinement with planar bundle adjustment and *BADGR* Li et al. [2025]. To isolate the learned representation before post-processing, we additionally evaluate raw *MOIS* prediction quality in the supplementary material. Baseline implementation details, `HM3D-XV` transfer results, and additional ablations are also provided in the supplementary material.

5.1 Pose Estimation Evaluation on ZInD-XV

We compare *MvFFN* with *CovisPose+Greedy Spanning Tree* (*GST*) Nejatishahidin et al. [2023], Li et al. [2025] and *VGGT* Wang et al. [2025] on `ZInD-XV`. We adapt the pretrained *VGGT* without fine-tuning: each panorama is decomposed into 12 overlapping perspective crops (six yaw directions at two pitches), all crops from all panoramas are processed jointly, and their poses are robustly aggregated into one planar pose per panorama. Full projection, metric-scale recovery, and aggregation details are provided in Appendix G.1. We exclude *GraphCovis* Nejatishahidin et al. [2023] and *PanoPose* Tu et al. [2024] because public code is unavailable. For each view-count setting, we evaluate on 1,000 N-view test tuples using the pose-graph alignment protocol from prior work Nejatishahidin et al. [2023]; tuple construction details are provided in the supplementary material. Although pose estimation is not the primary target of *MvFFN*, Table 1 shows that it is comparable to *CovisPose+GST*: *CovisPose+GST* attains lower median errors, while *MvFFN* reduces mean error, variance, and hard-case failures. *VGGT* performs substantially worse in this sparse wide-baseline panorama setting. We did not train the HCM and *MOIS* heads on a frozen *VGGT* backbone; whether improved panorama adaptation can make this head-only configuration effective remains an open question.

Table 1: Camera pose evaluation on ZInD-XV dataset.

Methods	5v Pos (cm)↓			5v Rot (°)↓			8v Pos (cm)↓			8v Rot (°)↓		
	Mn	Std	Med	Mn	Std	Med	Mn	Std	Med	Mn	Std	Med
CovisPose+GST	12.6	23.3	**9.3**	1.3	0.9	**0.7**	17.3	37.3	**11.8**	1.9	1.6	**0.8**
VGGT	30.7	39.4	13.3	11.1	16.0	4.0	53.4	63.1	27.8	13.3	17.7	4.9
MvFFN	**12.5**	**10.8**	10.2	**1.2**	**0.6**	1.1	**17.0**	**15.6**	13.8	**1.3**	**0.8**	1.2

5.2 Floor Layout Estimation Evaluation on ZInD-XV

We compare *MvFFN* with modular floor-layout pipelines because no prior method directly predicts structured multi-room layouts from sparse, unposed N-view panoramas. As summarized in Table 2, each baseline composes pose estimation, geometric input construction, and layout vectorization: *CovisPose+GST* (*CP*) or ground-truth poses provide the pose input, while the final layout is produced by heuristic *LGT* post-processing (*LGT-PP*) or learning-based top-down vectorization with *RoomFormer* (*RF*) Yue et al. [2023] and *PolyRoom* (*PR*) Liu et al. [2024]. We additionally evaluate *DOP-Net* Shen et al. [2023] and *Bi-Layout* Tsai et al. [2024] as fixed-protocol *LGT-Net* front-end replacements, and a best-effort *NadirFloorNet* Pintore et al. [2025] reproduction with *CP* registrations and no view-count fine-tuning because no public ZInD checkpoint or training entry point is available. We exclude *VGGT* from layout evaluation because its pose accuracy is substantially worse than *CovisPose*; implementation and metric details are provided in the supplementary material.

Table 2: Floor-layout evaluation on ZInD-XV. Distance is in cm. Geom. denotes the intermediate geometric input and Layout denotes the vectorization backend. GT-pose replaces the modular pipeline's estimated poses with ground-truth poses, isolating pose error. GT masks replace MvFFN's CovisPose-induced attention masks with ground-truth masks, testing sensitivity to that geometric prior. Bold marks the best result without ground-truth inputs; – denotes an unreported junction distance.

Method / Pipeline			5-view wall				5-view junction				8-view wall				8-view junction			
pose	geom.	layouts	Prec.↑	Rec.↑	F1 ↑	Dist ↓	Prec.↑	Rec.↑	F1 ↑	Dist ↓	Prec.↑	Rec.↑	F1 ↑	Dist ↓	Prec.↑	Rec.↑	F1 ↑	Dist ↓
MvFFN			**88.5**	**87.7**	**88.1**	**13.9**	**79.2**	**68.2**	**73.3**	**13.8**	**89.4**	**87.5**	**88.4**	**19.0**	**81.0**	**69.8**	**75.0**	**19.1**
CP		*RF*	31.9	44.2	37.1	84.9	15.4	20.9	17.7	137.8	35.0	42.4	38.3	79.0	15.7	18.6	17.0	136.8
CP		*PR*	33.6	29.3	31.3	86.6	17.4	14.9	16.1	129.7	31.8	25.0	28.0	86.2	13.8	10.5	11.9	133.4
CP	*NadirFloorNet*		64.7	61.6	63.1	30.8	46.3	43.3	44.8	–	64.0	65.8	64.9	33.8	47.9	47.7	47.8	–
CP	*LGT*	*LGT-PP*	75.6	71.4	73.4	21.3	60.0	54.8	57.3	21.3	76.3	72.7	74.5	24.4	61.7	56.7	59.1	24.4
CP	*DOP-Net*	*LGT-PP*	80.0	69.0	74.1	19.7	62.9	52.9	57.5	–	77.9	72.3	75.0	22.8	63.2	56.7	59.8	–
CP	*Bi-Layout*	*LGT-PP*	79.6	69.4	74.2	19.6	62.7	53.2	57.6	–	78.4	72.6	75.4	22.5	63.7	57.0	60.2	–
GT-pose	*LGT*	*LGT-PP*	78.8	70.5	74.4	19.2	62.4	54.3	58.1	19.7	80.5	70.8	75.3	22.7	65.1	55.5	59.9	22.7
MvFFN (GT masks)			88.9	87.9	88.4	14.0	79.4	67.9	73.2	13.9	87.8	87.1	87.4	19.2	79.2	69.2	73.9	19.1

We evaluate wall and junction precision, recall, and $F1$ with instance-level matching, and report matched-wall localization error; details are in the supplementary material. These structure-aware metrics are better suited to our setting than region IoU, since high-quality floor plan reconstruction requires accurate wall instances, junctions, connectivity, and geometric alignment, and *MvFFN* may produce either closed polygons or open wall sequences under limited view coverage Cruz et al. [2021]. As shown in Table 2, *MvFFN* substantially outperforms all modular baselines across both 5-view and 8-view settings. The strongest modern front-end substitution, *Bi-Layout*, reaches 74.2/57.6 wall/junction $F1$ at 5 views and 75.4/60.2 at 8 views, compared with 88.1/73.3 and 88.4/75.0 for *MvFFN*. *MvFFN* also outperforms *LGT-PP* with ground-truth poses, while replacing its CovisPose-induced attention masks with ground-truth masks changes accuracy by at most one point. Together, these controls show that stronger single-view boundaries, poses, or attention masks do not explain the margin; the remaining advantage comes from cross-view wall identity and ordered connectivity predicted by *MOIS* and assembled by *Layout Chaining*.

5.3 Global Refinement

We evaluate whether *MvFFN*'s predicted wall instances and pixel-to-wall correspondences support automatic downstream refinement. Table 3 reports matched-wall distance before and after planar bundle adjustment (*BA*) and *BADGR* Li et al. [2025], both over all samples and over the subset improved by each method. Planar bundle adjustment improves a majority of samples in both 5-view and 8-view settings, with clear gains on the improved subset. Overall gains are modest, and *BADGR* is more sensitive to initialization because it assumes complete initial room layouts and clean correspondences. Details are provided in the supplementary material.

Table 3: Matched-wall distance before and after refinement on ZInD-XV. Distances are in cm.

View	Method	All samples				Improved samples				
		Mean dist		Med. dist		Improved	Mean dist		Med. dist	
		before	after	before	after	(%)	before	after	before	after
5-view	*MvFFN+BA*	13.9	**13.7**	6.9	**6.7**	**68.0%**	14.8	**12.3**	7.5	**5.9**
	MvFFN+BADGR	13.9	17.7	6.9	8.1	**45.9%**	16.2	**14.1**	8.2	**6.2**
8-view	*MvFFN+BA*	19.0	**18.8**	8.8	8.8	**66.0%**	20.6	**17.8**	9.7	**8.2**
	MvFFN+BADGR	19.0	21.0	10.1	10.4	**48.5%**	22.9	**20.0**	8.8	**8.8**

6 Ablation Studies

We evaluate three complementary ablations. This section studies **architecture**, testing whether the two-branch, two-stage *MvFFN* design is necessary for stable *MOIS* prediction, and **prediction window**, testing how longer ordered wall sequences affect accuracy. Appendix E.1 studies **inductive bias**, evaluating rotation and correspondence priors across input-view counts.

Architecture. We ablate two core design choices in *MvFFN*: a dedicated semantic branch for *MOIS* prediction and the two-stage geometry-to-semantics training strategy. Table 4 compares four variants: a shared-encoder model, a two-branch model without geometry-to-semantic fusion, a full architecture trained in one stage, and the full two-stage *MvFFN*. The results show that both geometry-conditioned semantic reasoning and staged training are critical: removing geometry-to-semantic fusion sharply reduces recall and $F1$, while shared features or single-stage training underperform and become unstable, indicating tension between dense geometry objectives and the semantic *MOIS* objective. The full two-stage design gives the best stability and final layout accuracy.

Table 4: Ablation study of *MvFFN* on ZInD-XV, comparing encoder design, geometry fusion, and staged training. – denotes pose metrics identical to *MvFFN*.

Method	Geom Enc	Sem Enc	Geom Fusion	Train Stages	5v pos (cm)↓			5v rot (°)↓			5v wall				5v junction			
					Mn	Std	Med	Mn	Std	Med	Prec↑	Rec↑	$F1$ ↑	Dist↓	Prec↑	Rec↑	$F1$ ↑	Dist↓
Shared-Enc	✓	✗	✗	2	35.8	50.1	26.4	2.1	1.3	2.0	86.4	69.8	77.2	31.2	72.9	50.4	59.6	39.9
No-Fusion	✓	✓	✗	2	–	–	–	–	–	–	**92.6**	22.7	36.5	28.0	**84.3**	14.4	24.6	21.4
1-stage	✓	✓	✓	1	46.8	50.5	30.1	2.5	1.5	1.9	87.7	71.9	79.0	33.9	75.8	53.1	62.5	44.1
MvFFN	✓	✓	✓	2	**12.5**	**10.8**	**10.2**	**1.2**	**0.6**	**1.1**	88.5	**87.7**	**88.1**	**13.9**	79.2	**68.2**	**73.3**	**13.8**

***MOIS* prediction window.** To select the prediction-window size, we train two additional *MvFFN* variants with 5 and 7 ordered wall slots (Table 5). *Layout Chaining* remains unchanged and uses only the first three slots, isolating the effect of the training target. Longer windows consistently reduce accuracy: 5-view wall $F1$ drops from 88.1 to 85.6 and 84.4, while 8-view junction $F1$ drops from 75.0 to 71.3 and 67.1; 8-view matched-wall distance also worsens. Thus, the 3-wall window is the best operating point: compact local prediction is easier under sparse views, whereas longer sequences accumulate ambiguity from occlusion, room boundaries, and distant structure.

Table 5: *MvFFN* layout accuracy reported on 5- and 8-view test set from ZInD-XV. The model is trained to predict different numbers of adjacent walls in *MOIS* prediction.

# walls	5-view wall				5-view junction				8-view wall				8-view junction			
	Prec↑	Rec↑	$F1$ ↑	Dist↓	Prec↑	Rec↑	$F1$ ↑	Dist↓	Prec↑	Rec↑	$F1$ ↑	Dist↓	Prec↑	Rec↑	$F1$ ↑	Dist↓
3-wall	88.5	**87.7**	**88.1**	**13.9**	**79.2**	**68.2**	**73.3**	**13.8**	**89.4**	**87.5**	**88.4**	**19.0**	**81.0**	**69.8**	**75.0**	**19.1**
5-wall	**88.7**	82.8	85.6	14.7	78.8	64.2	70.8	17.0	88.4	83.7	86.0	19.6	79.4	64.7	71.3	23.2
7-wall	87.6	81.4	84.4	16.2	76.3	58.7	66.4	18.7	87.7	78.9	83.1	19.2	77.9	59.0	67.1	21.7

7 Qualitative Results

Qualitative results in Fig. 3 show representative 8-view reconstructions, with additional examples provided in Appendix J. Across simple and complex multi-room scenes, *MvFFN* produces more complete and globally consistent layouts than the strongest modular baseline, *LGT-Net* with *CovisPose*. The predicted wall instances are color-coded to show cross-view consistency. Compared with the baseline, *MvFFN* better preserves room shape, avoids duplicate or fragmented walls, and recovers neighboring structure visible through doorways under partial occlusion.



Figure 3: Qualitative comparisons on ZInD-XV test set. We show the strongest modular baseline, *LGT-Net* with *CovisPose*.

8 Conclusion

We introduced *MvFFN*, which reconstructs structured floor plans and camera poses from sparse, unposed 360° panoramas by predicting cross-view wall instances and within-room connectivity before global assembly. Experiments show clear gains over modular baselines, demonstrate automatic downstream refinement from predicted wall correspondences, and introduce ZInD-XV for future structured multi-view layout research.

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