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# DAGE: Dual-Stream Architecture for Efficient and Fine-Grained Geometry Estimation

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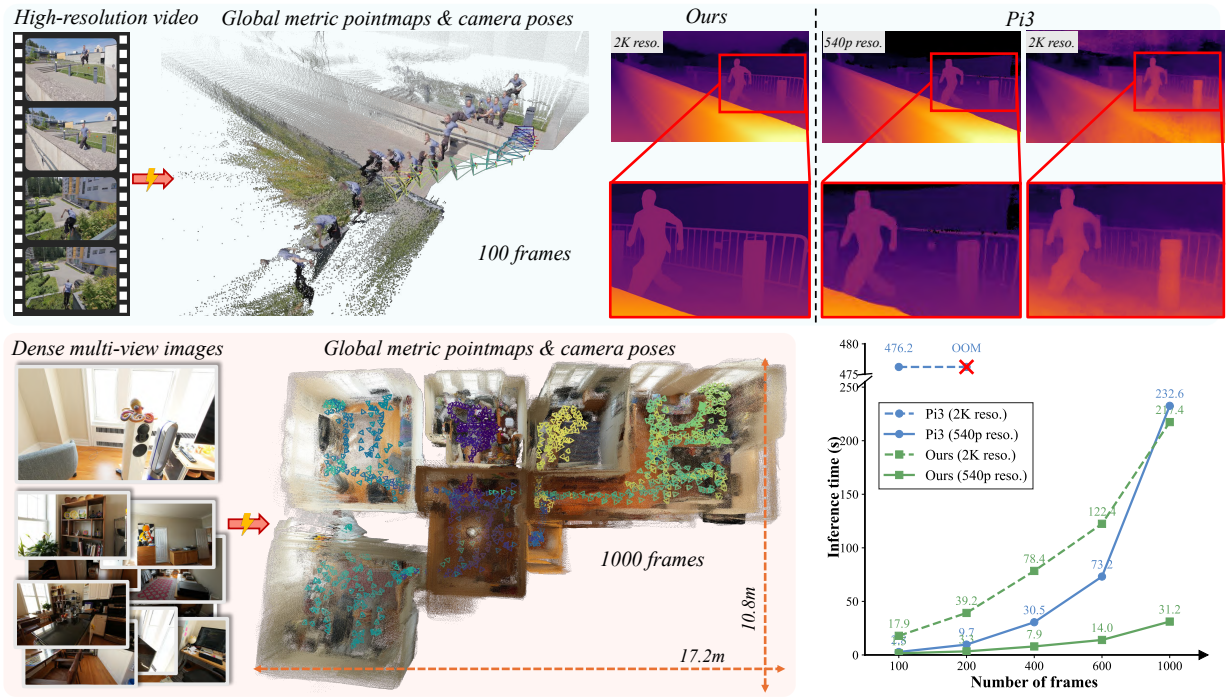



Figure 1. **DAGE** produces *high-resolution, fine-grained, metric-scale* and *cross-view consistent* 3D geometry together with accurate camera poses from visual inputs. It runs substantially faster than prior models [74, 79] and scales to long sequences (up to 1000 frames).

## Abstract

*Estimating accurate, view-consistent geometry and camera poses from uncalibrated multi-view/video inputs remains challenging—especially at high spatial resolutions and over long sequences. We present **DAGE**, a dual-stream transformer whose main novelty is to disentangle global coherence from fine detail. A **low-resolution** stream operates on aggressively downsampled frames with alternating frame/global attention to build a view-consistent representation and estimate cameras efficiently, while a **high-resolution** stream processes the original images per-frame to preserve sharp boundaries and small structures. A lightweight **adapter** fuses these streams via cross-attention, injecting global context without disturbing the pretrained single-frame pathway. This design scales resolution and clip length* independently*, supports inputs up to 2K, and maintains practical inference cost. DAGE delivers sharp depth/pointmaps, strong cross-view consistency, and accurate poses, establishing new state-of-the-art results for video geometry estimation and multi-view reconstruction.*

## 1. Introduction

Estimating 3D geometry and camera poses from multi-view images is a fundamental problem in computer vision. We target the demanding regime of *uncalibrated, high-resolution* inputs with potentially *thousands of frames*. This task is particularly challenging, as the model must simultaneously (i) enforce global consistency across views, (ii)

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preserve fine-grained details at high resolution, and (iii) remain tractable in runtime and memory for long sequences.

On one hand, feed-forward visual geometry networks [37, 68, 74, 75, 79, 85, 93] have achieved remarkable progress in globally consistent multi-view geometry estimation, setting new state-of-the-art results on various benchmarks [14, 67], including video depth estimation, 3D reconstruction, and camera pose prediction. However, their typically heavy network architectures limit training and inference to modest image resolutions (e.g., long side $\leq$ 518px) and a small number of input views, which leads to blurred thin structures and poorly defined object boundaries. Several works have adopted post-training acceleration strategies [22, 62, 73] to reduce computational cost and support more views during inference, yet they do not address the loss of high-frequency details or the tendency toward over-smoothed surfaces near edges and small objects.

On the other hand, single-view geometry estimators [6, 76, 77, 86, 87] operate flexibly at high resolution and produce sharp, detail-rich depth/pointmaps from single images, yet they lack temporal and multi-view consistency by design. Attempts to adapt these models to handle videos [12, 35, 38, 41, 45, 84] introduce heavy pipelines, and typically do not recover accurate camera poses. As a result, they fail to assemble a globally consistent 3D scene geometry directly from the feed-forward predictions.

Based on this observation, we present DAGE, a **D**ual-stream **A**rchitecture for efficient and fine-grained **G**eometry **E**stimation that meets the above criteria. It comprises two parallel streams and a lightweight fusion adapter. The **Low-Resolution (LR) Stream** focuses on extracting globally consistent features and predicting camera poses. It is composed of a ViT backbone followed by a global transformer with alternating frame-global attention [74, 79], which processes the entire sequence at a lower spatial resolution. Although the global transformer is computationally intensive, operating at low resolution keeps it tractable while preserving global context. The **High-Resolution (HR) Stream** is designed to capture high-frequency details and fine-grained features. It employs a ViT [18] that processes each image independently at its native resolution. Finally, our proposed **Lightweight Adapter** synchronizes and fuses LR and HR tokens before the dense heads, yielding geometry that is both globally consistent and richly detailed.

This decoupled design grants two critical advantages. *First, it achieves global consistency and tractability.* By restricting the computationally-heavy global attention to the LR stream, we alleviate the quadratic scaling bottleneck of global transformers [74, 79]. This significantly reduces runtime, by 2$\times$ and 28$\times$ at 540p and 2K resolutions, respectively, enabling our model to process thousands of frames. *Second, it preserves high-fidelity detail.* The HR stream operates per-frame, allowing it to scale to any resolution (e.g., up to 2K) and leverage priors from state-of-the-art single-image models for sharp detail and strong real-world generalization. In contrast to standard pipelines [74, 79, 85, 93] that couple image resolution with sequence length, DAGE decouples the two, enabling independent control over spatial detail and multi-view coherence, with a tractable runtime (see Fig. 1).

We validate our method and design choices through extensive experiments. DAGE achieves state-of-the-art performance on video geometry and depth-sharpness benchmarks, and is competitive on 3D reconstruction and camera pose estimation—while offering higher throughput and a lower GPU memory footprint. In summary, our technical contributions are twofold:

- A *dual-stream transformer* that couples a per-frame, high-resolution detail path with a multi-view, low-resolution global-attention path.
- A lightweight *Adapter* that fuses the two streams to produce sharp yet globally consistent geometry.

## 2. Related Work

**Single-view Geometry Estimation** aims to recover 3D scene geometry from a single image. Early approaches relied on handcrafted features and probabilistic models [32, 34, 59, 60]. With deep networks, numerous architectures were proposed [3, 19, 23, 42, 72], yet their generalization remained limited. The introduction of relative-depth [57] enabled training on large, mixed datasets, leading to strong zero-shot performance [4, 6, 29, 33, 55, 86, 87, 91]. However, many such methods require camera intrinsics and metric scale to recover absolute 3D geometry. Recent work addresses this by jointly estimating depth and intrinsics [6, 55, 90]. A complementary line of research regresses dense *3D pointmaps* directly [76, 77], from which depths and intrinsics can be recovered. Despite impressive single-image results, these methods typically exhibit temporal jitter and inconsistent scale when applied to videos.

**Fine-Grained Geometry Estimation** targets predicting sharper depth/pointmaps with high-frequency detail. Patch-wise fusion methods [46, 50] enhance local detail by combining per-patch estimates, but often introduce stitching artifacts at patch boundaries. Another line of work leverages powerful generative priors [56, 58] to produce highly detailed depth [24, 25, 30, 36, 54]. Depth Anything V2 [87] improves detail via large-scale, high-quality synthetic data, while DepthPro [6] employs a multi-patch ViT design [18] to better capture fine structures. MoGe2 [77] combines synthetic and refined real-world annotations with a coarse-to-fine loss [76], achieving strong metric accuracy and sharp predictions. *Concurrently*, [83] integrates foundation-model geometry priors [74, 87] with a cascaded DiT [53], yielding *pixel-perfect depth*. Nonetheless, these

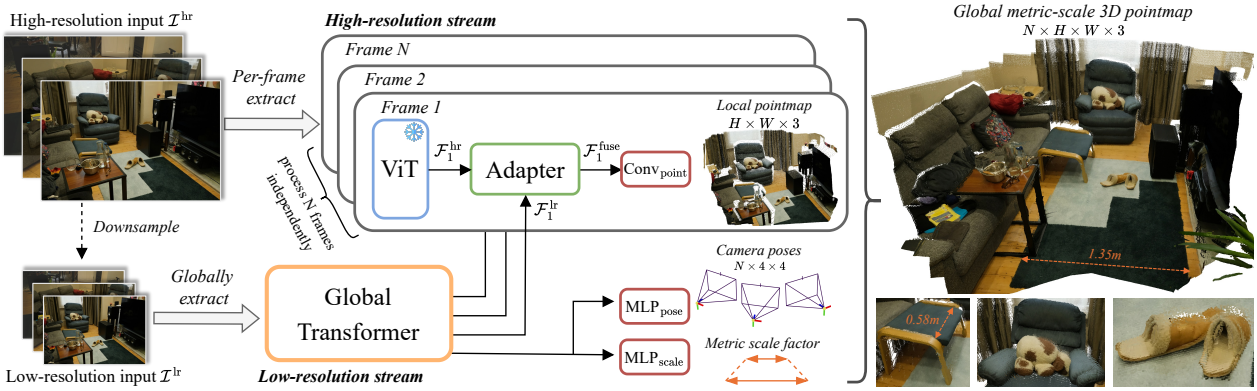



Figure 2. **Overview of DAGE.** Given a set of *unposed* RGB images, the model predicts per-frame pointmaps and camera poses, plus a scene-wise metric scale. The architecture has two parallel streams: (i) a low-resolution stream (lower part) that processes downsampled inputs to aggregate global context and regress poses/scene scale; and (ii) a high-resolution stream (upper part) that processes frames independently at native resolution to preserve fine detail. A lightweight Adapter fuses LR and HR tokens before the dense geometry head.

methods are predominantly per-image and fail to ensure temporal consistency in video setting.

**Video-based Geometry Estimation** mitigates temporal jitter and scale inconsistency by stabilizing *per-frame* predictions with test-time procedures or using video architectures. Several works regularize single-image depth across time using geometric consistency or online refinement [39, 40, 48, 69], or optimize scale/shift to co-align frames [35]. [9, 13, 41] add temporal heads or video transformers on top of pretrained single-view models, and diffusion-based pipelines [5, 31, 88] leverage strong video priors for temporally consistent depth. Despite impressive performance, diffusion-based methods are compute-intensive and typically do not recover camera poses.

**Visual Geometry Estimation** regresses both camera poses and the 3D scene structure from uncalibrated images or videos. Classical SfM/MVS pipelines [1, 61, 64, 81], are robust but require multi-stage optimization. [10, 51, 89] inject motion priors (e.g. optical flow, point tracking) and then perform bundle adjustment, which reduces manual engineering but requires per-video optimization. Dust3R [78] introduced a learning-based alternative that predicts pointmaps for image pairs in a shared coordinate frame and stitches multi-view input via a global alignment step. Subsequent work improves metric-scale recovery [43], extends to dynamic scenes [11, 21, 47, 92], and scales multi-view processing [20, 37, 68, 74, 75, 79, 82, 85, 93, 94]. Among these, VGGT [74] and Pi3 [79] demonstrate state-of-the-art performance with alternating global-frame attention transformers. However, the quadratic cost of global attention imposes tight token budgets, limiting input resolution and the number of frames; thus, predicted depth often appears blurred and fine structures are smoothed.

In contrast, our dual-stream approach performs feed-forward global aggregation on LR inputs for efficiency while preserving HR detail via a per-frame stream, with a lightweight adapter to fuse these two.

## 3. Method

### 3.1. Problem Definition

Given an *uncalibrated* set of $N$ RGB images $\mathcal{I} = \{I_i\}_{i=1}^N$ of a scene, where each $I_i \in \mathbb{R}^{H \times W \times 3}$, our model aims to reconstruct the 3D scene geometry by predicting three components: (1) per-frame pointmaps $\mathcal{P} = \{P_i\}_{i=1}^N$, where $P_i \in \mathbb{R}^{H \times W \times 3}$ represents the 3D coordinates of each pixel in the local camera coordinate system; (2) camera poses $\mathcal{G} = \{G_i\}_{i=1}^N$, where $G_i \in \text{SE}(3)$ encodes each camera's rotation and translation; and (3) a single global metric scale factor $s \in \mathbb{R}^+$.

State-of-the-art feed-forward approaches [74, 79] are constrained by the high computational cost of global attention. This typically limits their inputs to modest resolutions (e.g., 518px on the long side) and short sequences (e.g., $N < 200$). We address this limitation with a dual-stream architecture designed to produce high-quality, fine-grained 3D geometry and accurate camera poses while supporting flexible spatial resolutions and long sequences.

Fig. 2 illustrates the overall architecture of our model. It consists of a *low-resolution (LR) stream* (Sec.3.2) and a *high-resolution (HR) stream* (Sec.3.3), which operate in parallel and are synchronized through a lightweight adapter (Sec.3.4), followed by dense prediction heads (Sec.3.5). The LR stream extracts globally consistent features and estimates camera poses, while the HR stream predicts per-frame pointmaps at the native input resolution. The global features produced by the LR stream are injected into the HR stream via the adapter to enhance geometric consistency across views. Training details are described in Sec.3.6.

### 3.2. Low-Resolution Stream

The low-resolution stream is responsible for enforcing global consistency and estimating camera poses. It pro-

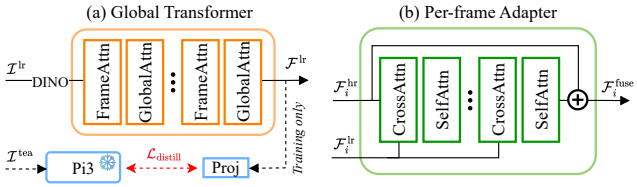



Figure 3. The **Global transformer** (left) operates on low-resolution inputs with alternating global and frame-wise attention; during training, feature distillation compensates for aggressive downsampling. The **Adapter** (right) stacks cross and self-attention blocks to fuse multi-view–consistent LR tokens into the HR stream.

cesses the entire sequence $\{I_i\}$ at a fixed low resolution (long side $\leq 252$px), $\mathcal{I}^{\text{lr}}$. These images are passed through a global transformer to output *LR feature tokens* $\mathcal{F}^{\text{lr}} \in \mathbb{R}^{N\times h_{lr}\times w_{lr}\times C}$. This global transformer (Fig. 3a) consists of a DINOv2 [52] tokenizer, and alternating blocks of frame-wise and global self-attention (`[FrameAttn → GlobalAttn]`) [74, 79], which is effective for capturing scene-level structure. We do not use dedicated camera tokens, preserving permutation equivariance [79].

While low-resolution processing ensures tractability, training the LR stream from scratch often leads to degraded camera pose accuracy. To address this, we leverage the rich global representations of a pre-trained teacher model, Pi3 [79], through knowledge distillation. Specifically, the teacher processes a higher-resolution input $\mathcal{I}^{\text{tea}}$ (capped at 518px to match [74, 79]) and produces features $\mathcal{F}^{\text{tea}} \in \mathbb{R}^{N\times h_{\text{tea}}\times w_{\text{tea}}\times C}$. These features are then used to supervise the LR stream via a feature distillation loss:

$$\mathcal{L}_{\text{dis}} = 1 - \text{sim}(p_\phi(\mathcal{F}^{\text{lr}}), \mathcal{F}^{\text{tea}}) \tag{1}$$

where $\text{sim}(\cdot,\cdot)$ is the cosine similarity function, and $p_\phi$ is a projection network mapping student features to the teacher's representation space and spatial dimension.

### 3.3. High-Resolution Stream

The high-resolution stream processes each frame of the input sequence $\{I_i\}$ independently at its original resolution. To preserve fine-grained detail and strong zero-shot generalization capabilities, we adopt MoGe2 [77] as the HR backbone. This model uses a 24-layer ViT encoder [18] to extract the *HR feature tokens* $\mathcal{F}^{\text{hr}} \in \mathbb{R}^{N\times h_{hr}\times w_{hr}\times C_{hr}}$.

### 3.4. Adapter

The adapter (Fig. 3b) is designed to inject global context from the LR stream into the per-frame HR stream. A naive solution—such as upsampling LR features via interpolation and concatenating them with HR features—often introduces artifacts and fails to capture meaningful cross-view relations. Alternative approaches, including pixel-shuffle upsampling [15, 83] or CNN-based upsampling [66], alleviate such artifacts but rely on a fixed scale factor, which is too restrictive for inputs that may vary up to 2K resolution.

To overcome these limitations, we adopt a more flexible *cross-attention* mechanism that accommodates arbitrary token counts from both streams. This fusion is followed by HR self-attention to restore per-frame spatial coherence. Concretely, for each $i$-th frame, the fused feature $\mathcal{F}_i^{\text{fuse}}$ is computed as:

$$\mathcal{F}_i^{\text{fuse}} = \text{CrossAttn}\big(Q = \mathcal{F}_i^{\text{hr}};\, K, V = \mathcal{F}_i^{\text{lr}}\big) \tag{2}$$

$$\mathcal{F}_i^{\text{fuse}} = \mathcal{F}_i^{\text{hr}} + \text{MLP}\big(\text{SelfAttn}(\mathcal{F}_i^{\text{fuse}})\big) \tag{3}$$

Positional encodings are applied before attention to align HR patch coordinates with their LR counterparts, stabilizing the cross-scale fusion. We stack five such `[CrossAttn → SelfAttn]` blocks.

We employ Rotary Positional Encodings (RoPE) for all attention layers, but with different strategies for self-attention and cross-attention to handle varying resolutions. **Self-Attention:** Standard RoPE does not extrapolate well to spatial dimensions larger than those seen during training, which can cause distortion on high-resolution inputs [74, 75, 79]. Thus, we adopt the *interpolated RoPE* [8] technique. We define a fixed maximum patch length, $l^{\max}$. At both training and inference, we rescale the angular frequencies of the positional encoding to this fixed context size, which keeps the positional spectrum stable even at very high resolutions. **Cross-Attention:** A challenge is the large spatial mismatch between the LR and HR streams (e.g., 252px vs. 2K). To align them, we "snap" each HR token to its nearest grid cell in the LR feature map. The HR token then uses the positional encoding from that corresponding LR cell. This simple strategy effectively matches patches across scales and avoids extrapolation, as the LR stream's spatial dimensions are always fixed and within the trained bounds. Concretely, let $R(\mathbf{f}, \mathbf{m})$ be the RoPE function applied to token $\mathbf{f}$ at 2D position $\mathbf{m}$. The modified RoPE functions are:

$$R_{\text{self}}\big(\mathbf{f}^{\text{hr}}, \mathbf{m}^{\text{hr}}\big) = R\big(\mathbf{f}^{\text{hr}},\, \mathbf{m}^{\text{hr}} \cdot l^{\max}/l^{\text{hr}}\big)\,, \tag{4}$$

$$R_{\text{cross}}\big(\mathbf{f}^{\text{hr}}, \mathbf{m}^{\text{hr}}\big) = R\Big(\mathbf{f}^{\text{hr}},\, \text{sampling}\Big(\mathbf{m}^{\text{hr}},\, \text{grid}^{\text{lr}}\Big)\Big) \tag{5}$$

where $l^{\text{hr}}$ is the side length of the HR grid.

**Adapter Design Discussion.** We investigated various strategies for fusing the LR and HR tokens, focusing on *where* and *how* to inject the global information. For *where* to insert, one approach is to inject intermediate LR features into each ViT layer of the HR stream. This mitigates scale drift but fails to enforce cross-view global consistency (see Sec. 4.6). For *how* to fuse, we considered alternatives like concatenation and addition with learnable interpolation. We find that the best trade-off is a lightweight adapter after the HR ViT encoder, comprising cross-attention to inject global context and self-attention to re-calibrate intra-frame coherence (see Sec. 4.6). This strategy preserves the HR stream's original feature space at the start of training, allowing the model to gradually learn to incorporate the multi-view consistent constraints to refine the final geometry.

### 3.5. Prediction Heads

**Dense Geometry.** We employ a feature pyramid of convolutional layers [77] to gradually upsample the per-patch features $\mathcal{F}^{\text{fuse}}$ into dense feature maps at the original image resolution to regress the pointmaps $\mathcal{P}$. This convolutional-style head yields smoother predictions, avoiding the grid-like artifacts observed in [79] (see Fig. 5).

**Camera Pose.** We regress the per-frame camera parameters using the LR features $\mathcal{F}^{\text{lr}}$. This is done for efficiency, as camera poses do not require fine-grained features. Following [17, 79], we use average pooling and an MLP to regress the translation and rotation in a 9D representation [44].

**Metric Scale.** We add a *metric scale* token in the video transformer, followed by an MLP to predict a single metric scale factor for each scene.

### 3.6. Training Details

#### 3.6.1. Training loss

We train the model with a combination of pointmap, camera, scale, normal, gradient, and distillation losses.

**Pointmap loss.** We predict a per-pixel 3D point $\hat{\mathbf{p}}_{i,j}$ up to a scene-wide scale. Let $\text{norm}(\cdot)$ denote a scene normalization (distance-to-origin) applied to both prediction and ground truth. We compute a single alignment scale $s^*$ using the ROE solver [76] and supervise with an $\ell_1$ loss:

$$\mathcal{L}_{\text{pm}} = \frac{1}{NHW} \sum_{i=1}^{N} \sum_{j=1}^{H\times W} \left\| \frac{s^* \hat{\mathbf{p}}_{i,j}}{\text{norm}(\hat{\mathcal{P}})} - \frac{\mathbf{p}_{i,j}}{\text{norm}(\mathcal{P})} \right\|_1 . \quad (6)$$

Unlike uncertainty-weighted objectives used in [74, 78], we do *not* attenuate errors with confidences, as we found this can suppress hard structures and reduce sharpness.

**Camera loss.** Following [79], we supervise *relative* camera poses to avoid fixing a global coordinate frame. Let $\hat{\mathbf{g}}_{uv}$ and $\mathbf{g}_{uv}$ denote predicted and ground-truth pairwise poses between frames $u$-th and $v$-th, the camera loss is defined as:

$$\mathcal{L}_{\text{camera}} = \frac{1}{N(N-1)} \sum_{\substack{u,v=1 \\ u\neq v}}^{N} \mathcal{L}_{\text{cam}}(\hat{\mathbf{g}}_{uv}, \mathbf{g}_{uv}), \quad (7)$$

where $\mathcal{L}_{\text{cam}}$ comprises $\mathcal{L}_{\text{rot}}$ that minimizes the geodesic distance of the rotation part, and $\mathcal{L}_{\text{trans}}$ is the $\ell_1$ loss of the translation part.

**Scale loss.** For datasets with metric supervision, we additionally supervise the predicted metric scale $\hat{s}$:

$$\mathcal{L}_{\text{scale}} = \left\| \log \hat{s} - \log \left( s^* \frac{\text{norm}(\mathcal{P})}{\text{norm}(\hat{\mathcal{P}})} \right) \right\|_2 . \quad (8)$$

**Normal loss.** To encourage locally smooth but faithful surfaces, we supervise normals computed *on-the-fly* from the pointmap via cross products [76]:

$$\mathcal{L}_{\text{normal}} = \frac{1}{NHW} \sum_{i=1}^{N} \sum_{j=1}^{H\times W} \angle(\hat{\mathbf{n}}_{i,j}, \mathbf{n}_{i,j}), \quad (9)$$

where $\angle(\cdot,\cdot)$ is the angular difference.

**Gradient loss.** To improve local geometry, MoGe [76] applies a *multi-scale affine-invariant pointmap loss* by subsampling local regions at several scales and aligning each region to ground truth independently. While this improves single-image sharpness, we found that per-region independent alignments introduce patch-wise degrees of freedom that break cross-view consistency, leading to seams and drift—undesirable in our multi-view setting (see Tab. 6b). Instead, we preserve a *single global alignment* and encourage detail by supervising *image gradients* of the canonical inverse depth [6] at multiple scales:

$$\mathcal{L}_{\text{gradient}} = \frac{1}{NHW} \sum_{i=1}^{N} \sum_{j=1}^{H\times W} \left\| \nabla \hat{d}_{i,j} - \nabla d_{i,j} \right\|_1 , \quad (10)$$

where $\hat{d}$ and $d$ denote ground-truth and predicted canonical inverse depth, respectively, and $\nabla$ is the Scharr and Laplace gradient filters.

Due to the sparsity of real-world depth annotations, we only apply the normal and gradient loss on synthetic data.

#### 3.6.2. Implementation details

The HR stream uses a frozen 24-layer ViT from MoGe2 [77]. Since our training corpus is relatively small, we initialize the LR stream from Pi3 [79] instead of training from scratch. The adapter comprises five blocks, each containing a cross-attention and self-attention layer. We train DAGE on 18 publicly available datasets spanning indoor/outdoor, static/dynamic scenes. The complete list of datasets and implementation details are provided in the supplementary.

## 4. Experiments

This section compares our method to state-of-the-art approaches across four tasks to show its effectiveness.

### 4.1. Video Geometry Estimation

We evaluate on eight datasets spanning diverse conditions—GMU Kitchens [27], ScanNet [16] (indoor RGB-D), KITTI [26] (outdoor driving with LiDAR), Sintel [7] and Monkaa [49] (synthetic with precise depth and challenging dynamics), and the high-resolution UrbanSyn [28], Unreal4K [70], and Diode [71]-and resolutions from ∼640p to 2K. Following [76, 84], we report relative point error $\text{Rel}^p \downarrow$ and inlier ratio $\delta^p \uparrow$ at a 0.25 threshold, and evaluate *affine-invariant* pointmaps by aligning predictions to ground truth with a single, shared scale and shift per video. We compare against single-image methods [6, 76, 77], video diffusion-based model [84], and set-based visual-geometry models [74, 75, 79]. For methods that do not

Table 1. **Video pointmap evaluation**. Results are aligned with the ground truth by optimizing a shared scale and shift factor across the entire video. "MV/HR/PO" indicate multi-view support, high-resolution input support, and whether the method predicts camera poses. We mark best and second-best.

| Method | MV | HR | PO | GMU [27] (960 × 512) | | Monkaa [49] (960 × 512) | | Sintel [7] (896 × 448) | | ScanNet [16] (640 × 512) | | KITTI [26] (768 × 384) | | UrbanSyn [28] (2048 × 1024) | | Unreal4K [70] (1920 × 1080) | | Diode [71] (1024 × 768) | | Rank ↓ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | $\text{Rel}^p$ ↓ | $\delta^p$ ↑ | |
| DepthPro [6] | | ✓ | | 9.5 | 93.9 | 25.1 | 58.4 | 40.8 | 44.7 | 9.3 | 94.9 | 10.0 | 94.9 | 48.9 | 40.1 | 74.7 | 12.0 | 32.4 | 59.2 | 7.9 |
| MoGe [76] | | ✓ | | 20.3 | 71.2 | 22.9 | 61.3 | 29.4 | 59.8 | 13.4 | 88.0 | 8.0 | 95.8 | 14.9 | 87.0 | 38.3 | 51.5 | 31.8 | 52.9 | 7.4 |
| MoGe2 [77] | | ✓ | | 19.6 | 72.4 | 25.0 | 57.0 | 29.8 | 58.4 | 12.4 | 89.4 | 9.0 | 97.2 | 13.4 | 90.0 | 32.9 | 59.1 | 31.0 | 54.2 | 6.8 |
| MoGe2 [77]† | △ | ✓ | | 7.1 | 94.6 | 21.4 | 67.6 | 28.2 | 62.8 | 7.8 | 97.5 | 10.5 | 98.4 | 7.2 | 97.1 | 12.6 | 86.7 | 15.8 | 84.1 | 4.1 |
| CUT3R [75] | ✓ | | ✓ | 8.0 | 93.7 | 31.8 | 47.5 | 35.8 | 47.5 | 5.9 | 97.9 | 14.5 | 87.5 | 21.6 | 68.6 | 16.8 | 79.6 | 17.9 | 78.3 | 6.8 |
| VGGT [74] | ✓ | | ✓ | 5.4 | 93.8 | 13.6 | 84.4 | 23.7 | 73.1 | 2.9 | 99.0 | 7.5 | 97.4 | 14.5 | 87.3 | 8.6 | 96.1 | 13.3 | 85.9 | 3.4 |
| Pi3 [79] | ✓ | | ✓ | 5.2 | 94.2 | 11.6 | 90.0 | 22.0 | 72.9 | 2.2 | 99.4 | 6.3 | 97.3 | 16.8 | 77.5 | 19.5 | 75.3 | 9.2 | 95.2 | 3.3 |
| GeoCrafter [84] | ✓ | △ | | 8.3 | 94.8 | 15.7 | 83.4 | 25.0 | 69.3 | 8.3 | 96.9 | 5.6 | 98.8 | 12.5 | 91.9 | 21.6 | 74.5 | 12.5 | 93.0 | 3.9 |
| **DAGE (ours)** | ✓ | ✓ | ✓ | 4.9 | 94.2 | 10.1 | 91.0 | 21.5 | 75.6 | 2.1 | 99.5 | 5.9 | 99.0 | 8.8 | 96.0 | 11.9 | 89.1 | 9.7 | 94.4 | 1.6 |

△: *partial support*. †: obtained by multiplying per-frame pointmap by predicted metric scale factor.

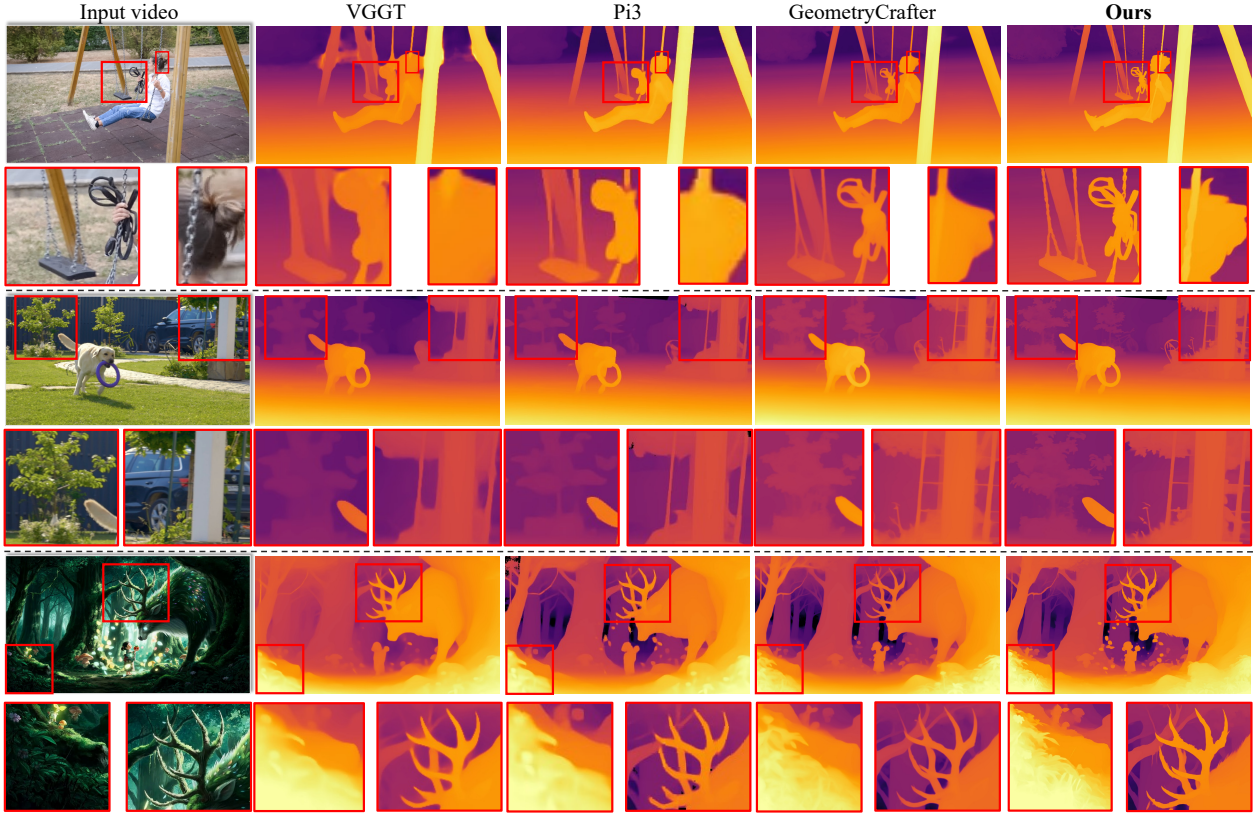



Figure 4. **Visual comparison of video depth on *in-the-wild* scenes.** We convert the depth map to a disparity map for better visualization, and zoom-in (red bounding boxes) to emphasize details. DAGE preserves sharp boundaries and fine-grained detail—especially for thin structures and small or distant objects, outperforming a diffusion-based baseline [84].

support high-resolution inference [74, 75, 79, 84], inputs are downsampled to the model's native resolution and outputs are upsampled to the original size to avoid degenerate predictions. In Tab. 1, DAGE delivers consistently strong performance across datasets—achieving state-of-the-art average rank on $\text{Rel}^p$ and $\delta^p$—with pronounced gains on high-resolution scenarios. We visualize the disparity map of our approach and other baselines in Fig. 4. Detailed evaluations (including *scale-invariant*, *affine-invariant* and video depth estimation) are provided in the supplementary.

## 4.2. Sharp Depth Estimation

We assess depth–boundary sharpness on four synthetic datasets with high-quality depth annotations —Monkaa [49], Sintel [7], UrbanSyn [28], and Unreal4K [70]. Following [6], we report the scale-invariant

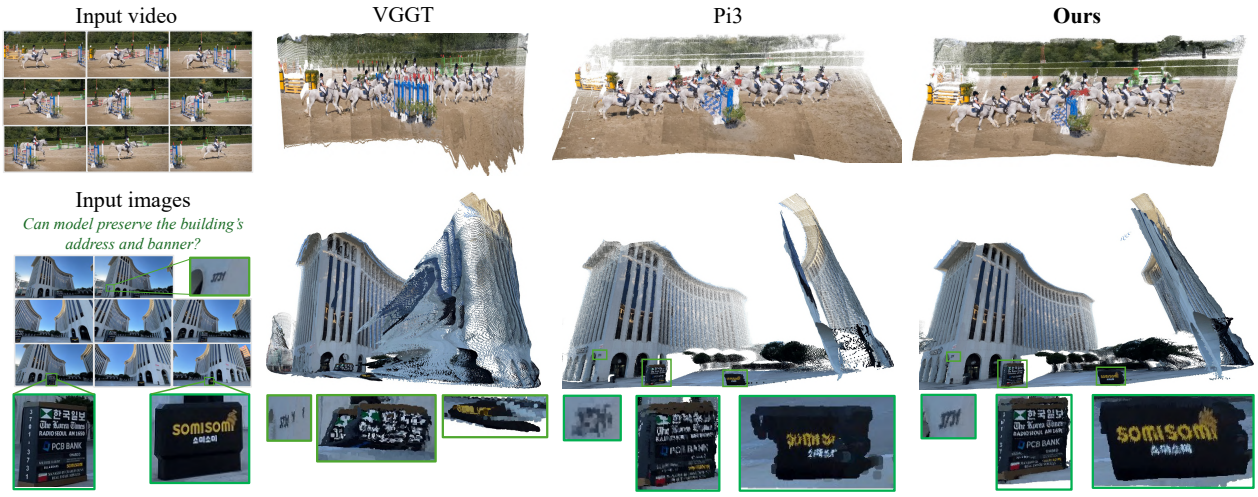



Figure 5. **Visual comparison of 3D reconstruction on *in-the-wild* scenes.** Compared to VGGT [74] and Pi3 [79], DAGE achieves comparable multi-view consistency while preserving markedly finer detail (green boxes).

boundary F1↑, which compares occlusion contours induced by neighboring-pixel depth ratios in prediction versus ground truth. Because F1 does not reflect temporal stability, we also measure the pseudo depth boundary error ($C_{\text{PDBE}}$ ↓) [54], defined as the Chamfer distance between prediction and ground-truth at canny-detected edges. For a fair comparison of sharpness detail, we evaluate methods at each dataset's native resolution; models that run out of memory (e.g., [74, 84]) are downsampled to the largest feasible resolution. Results in Tab. 2 show that, among methods producing temporally consistent video depth [74, 75, 79, 84], DAGE achieves the highest F1 and the lowest PDBE. While DepthPro [6] attains a higher F1 on some datasets, DAGE yields lower $C_{\text{PDBE}}$—indicating more temporally consistent boundaries in the video setting.

Table 2. **Sharpness depth evaluation**.

| Method | Monkaa [49] | | Sintel [7] | | UrbanSyn [28] | | Unreal4K [70] | |
|---|---|---|---|---|---|---|---|---|
| | F1↑ | $C_{\text{PDBE}}$ ↓ | F1↑ | $C_{\text{PDBE}}$ ↓ | F1↑ | $C_{\text{PDBE}}$ ↓ | F1↑ | $C_{\text{PDBE}}$ ↓ |
| DepthPro [6] | 0.19 | 21.3 | 0.41 | 17.0 | 0.14 | 12.5 | 0.07 | 116.4 |
| MoGe2 [77] | 0.27 | 11.6 | 0.27 | 10.1 | 0.09 | 19.1 | 0.10 | 35.2 |
| GeoCrafter [84] | 0.19 | 8.86 | 0.28 | 8.1 | 0.08* | 33.2* | 0.06* | 41.4* |
| CUT3R [75] | 0.08 | 20.3 | 0.11 | 16.5 | 0.01 | 44.0 | 0.01 | 63.1 |
| VGGT [74] | 0.14 | 11.1 | 0.20 | 9.6 | 0.02* | 42.0* | 0.03* | 38.1* |
| Pi3 [79] | 0.14 | 12.7 | 0.20 | 8.1 | 0.01 | 27.9 | 0.03 | 46.9 |
| **DAGE (ours)** | 0.29 | 10.1 | 0.34 | 7.8 | 0.09 | 17.8 | 0.14 | 33.1 |

*: *Input resolution downscaled to prevent out-of-memory (OOM).*

## 4.3. Multi-view Reconstruction

Following [75, 79], we evaluate reconstructed multi-view *pointmaps* on 7-Scenes [63] and NRGBD [2] under *sparse* and *dense* settings. Predictions are first aligned to ground truth via Umeyama $\text{Sim}(3)$, then refined with ICP. We report accuracy Acc.↓, completeness Comp.↓, and normal consistency NC↑ in Tab. 3. Comparisons include recent feed-forward visual-geometry methods [37, 74, 75, 79, 85, 93]. We also assess metric-scale reconstruction by aligning with rigid transformation $\text{SE}(3)$, comparing against metric-pointmap methods [37, 75]. Across sparse and dense settings, DAGE matches state-of-the-art performance [74, 79] while recovering metric-accurate geometry. Fig. 5 shows that our model produces globally consistent pointmaps while preserving fine-grained details.

## 4.4. Camera Pose Estimation

We evaluate on the synthetic Sintel [7] and two real-world datasets, TUM-Dynamics [65] and ScanNet [16]. We report *Absolute Trajectory Error* (ATE) and *Relative Pose Error* for translation/rotation ($\text{RPE}_T$/$\text{RPE}_R$). Predicted camera trajectories are registered to ground truth with a $\text{Sim}(3)$ alignment. We summarize the performance in Tab. 4. Notably, we run the LR stream at 252px (long side) to estimate poses efficiently. Competing methods [74, 75, 79] typically require 518px to achieve accurate predictions. Despite using lower resolution inputs, DAGE matches their performance at their high-res settings—and outperform them when evaluated at the same low-res setting.

## 4.5. Runtime Comparison

Tab. 5 reports the FPS and GPU memory consumption averaged over ten 100-frame videos on a single A100 GPU. DAGE sustains 65.4 FPS at 540p, which is 2× faster than Pi3, and remains tractable at 5.6 FPS on 2K, where global-attention baselines [74, 79] often run out of memory (*OOM*). It is consistently faster than multi-view methods [74, 75, 84] and adds only marginal overhead over the single-view MoGe2 [77]—thanks to the decoupled LR/HR design that confines heavy global attention to the LR path, keeping runtime largely insensitive to HR input size.

Table 3. **Multi-view reconstruction evaluation.** We report the *median* values on 3 settings, including *sparse*, *dense*, and *metric*.

| Method | Setting | 7-Scenes [63] | | | NRGBD [2] | | |
|---|---|---|---|---|---|---|---|
| | | Acc.↓ | Comp.↓ | NC↑ | Acc.↓ | Comp.↓ | NC↑ |
| Fast3R [85] | *sparse* | 0.065 | 0.089 | 0.759 | 0.091 | 0.104 | 0.877 |
| CUT3R [75] | *sparse* | 0.049 | 0.051 | 0.805 | 0.041 | 0.031 | 0.968 |
| FLARE [93] | *sparse* | 0.057 | 0.107 | 0.780 | 0.024 | 0.025 | 0.988 |
| VGGT [74] | *sparse* | 0.025 | 0.033 | 0.845 | 0.029 | 0.038 | 0.981 |
| Pi3 [79] | *sparse* | 0.029 | 0.049 | 0.841 | 0.015 | 0.014 | 0.992 |
| MapAny [37] | *sparse* | 0.053 | 0.064 | 0.83 | 0.064 | 0.058 | 0.946 |
| **DAGE (ours)** | *sparse* | 0.027 | 0.042 | 0.846 | 0.018 | 0.016 | 0.992 |
| Fast3R [85] | *dense* | 0.017 | 0.018 | 0.725 | 0.030 | 0.016 | 0.934 |
| CUT3R [75] | *dense* | 0.010 | 0.008 | 0.764 | 0.037 | 0.017 | 0.953 |
| FLARE [93] | *dense* | 0.007 | 0.013 | 0.785 | 0.011 | 0.008 | 0.986 |
| VGGT [74] | *dense* | 0.008 | 0.012 | 0.760 | 0.010 | 0.005 | 0.988 |
| Pi3 [79] | *dense* | 0.007 | 0.011 | 0.792 | 0.008 | 0.005 | 0.987 |
| MapAny [37] | *dense* | 0.008 | 0.008 | 0.780 | 0.018 | 0.010 | 0.970 |
| **DAGE (ours)** | *dense* | 0.007 | 0.009 | 0.793 | 0.009 | 0.006 | 0.985 |
| CUT3R [75] | *metric* | 0.189 | 0.186 | 0.582 | 0.307 | 0.253 | 0.606 |
| MapAny [37] | *metric* | 0.339 | 0.109 | 0.639 | 0.156 | 0.108 | 0.910 |
| **DAGE (ours)** | *metric* | 0.034 | 0.041 | 0.847 | 0.085 | 0.101 | 0.923 |

Table 4. **Camera pose evaluation**

| Method | Sintel [7] | | | TUM-dynamics [65] | | | ScanNet [16] | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATE↓ | $RPE_T$↓ | $RPE_R$↓ | ATE↓ | $RPE_T$↓ | $RPE_R$↓ | ATE↓ | $RPE_T$↓ | $RPE_R$↓ |
| Fast3R [85] | 0.371 | 0.298 | 13.75 | 0.090 | 0.101 | 1.425 | 0.155 | 0.123 | 3.491 |
| CUT3R [75] | 0.217 | 0.070 | 0.636 | 0.047 | 0.015 | 0.451 | 0.094 | 0.022 | 0.629 |
| FLARE [93] | 0.207 | 0.090 | 3.015 | 0.026 | 0.013 | 0.475 | 0.064 | 0.023 | 0.971 |
| VGGT [74] | 0.167 | 0.062 | 0.491 | 0.012 | 0.010 | 0.311 | 0.035 | 0.015 | 0.382 |
| Pi3 [79] | 0.074 | 0.040 | 0.282 | 0.014 | 0.009 | 0.312 | 0.031 | 0.013 | 0.347 |
| VGGT (252px) | 0.228 | 0.095 | 1.03 | 0.053 | 0.028 | 0.652 | 0.109 | 0.039 | 1.357 |
| Pi3 (252px) | 0.153 | 0.088 | 0.684 | 0.025 | 0.019 | 0.370 | 0.045 | 0.017 | 0.438 |
| **DAGE (ours)** | 0.132 | 0.051 | 0.406 | 0.014 | 0.010 | 0.323 | 0.031 | 0.014 | 0.389 |

Table 5. **Throughput comparison.** FPS↑ / GPU memory↓ (GB) measured on 100-frame clips per resolution.

| Resolution | MoGe2† | | GeoCrafter | | CUT3R | | VGGT | | Pi3 | | **DAGE** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FPS | Mem. | FPS | Mem. | FPS | Mem. | FPS | Mem. | FPS | Mem. | FPS | Mem. |
| 540×360 | 79.4 | 8.1 | 3.1 | 17.3 | 27.2 | 16.5 | 30.1 | 17.3 | 36.3 | 17.2 | 65.4 | 10.1 |
| 960×512 | 30.0 | 15.3 | 1.7 | 24.1 | 20.3 | 19.0 | 2.1 | 26.9 | 3.1 | 23.1 | 28.9 | 18.3 |
| 2048×1024 | 6.1 | 22.1 | *OOM* | | 4.5 | 33.2 | *OOM* | | 0.2 | 66.7 | 5.6 | 27.9 |

† : Methods that do *not* produce temporally consistent geometry.

### 4.6. Ablation Study

**Ablation on Adapter.** We investigate strategies to fuse *multi-view–consistent* LR tokens into *high-resolution, fine-grained* HR tokens (Tab. 6a). **Setting A (post-align):** per-frame MoGe2 [77] with *post hoc* alignment to a multi-view–consistent pointmap from a visual-geometry model (e.g., [79]), termed aligned MoGe2; this improves detail but leaves layering/stitching artifacts (see Supp.). **Setting B (interp+SA):** LR tokens interpolated to the HR grid, concatenated with HR tokens, then fused via several HR self-attention layers. **Setting C (all-CA):** adapter blocks use cross-attention only, with HR queries attending to LR keys/values at every block. **Setting D (Alter-Adapter):** a cross/self-attention module inserted after each of the last 5 ViT blocks in the HR stream. Overall, the proposed CrossAttn − SelfAttn adapter, inserted after the HR-stream ViT, consistently outperforms these variants, reducing artifacts and improving cross-view coherence.

Table 6. **Ablation studies** (a) different adapter design, (b) effect of each component on the depth sharpness

| Variant | Acc.↓ | Comp.↓ |
|---|---|---|
| A: Aligned MoGe2 | 0.031 | 0.028 |
| B: Interp+SA | 0.030 | 0.024 |
| C: All-CA | 0.021 | 0.018 |
| D: Alter-Adapter | 0.023 | 0.018 |
| **Ours** | **0.018** | **0.016** |

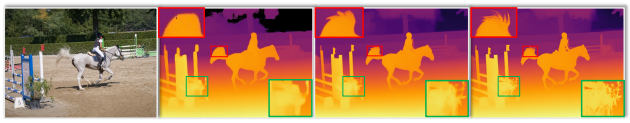
(a) Adapter design (NRGBD [2])

| Variant | F1↑ | $Rel^P$↓ | $\delta^P$↑ |
|---|---|---|---|
| Pi3 [79]+AnyUp [80] | 0.09 | 24.5 | 67.8 |
| **Ours** | **0.34** | 21.5 | **75.6** |
| − W/o mono. prior | 0.27 | 22.6 | 73.5 |
| − W/o gradient loss | 0.31 | 21.4 | 75.5 |
| + With local loss | 0.30 | **20.9** | 75.1 |

(b) Depth sharpness (Sintel [7])

Table 7. **Ablation study** on the LR stream resolution

| Reso. | Sintel [7] (pose) | | | Sintel [7] (depth) | | | NRGBD [2] | | FPS↑ |
|---|---|---|---|---|---|---|---|---|---|
| | ATE↓ | $RPE_T$↓ | $RPE_R$↓ | $Rel^P$↓ | $\delta^P$↑ | F1↑ | Acc.↓ | Comp.↓ | |
| 252px (default) | 0.132 | 0.051 | 0.406 | 21.5 | 75.5 | 0.34 | 0.018 | 0.016 | 65.4 |
| 252px (no distill) | 0.111 | 0.057 | 0.584 | 22.9 | 73.0 | 0.35 | 0.019 | 0.017 | 65.4 |
| 336px | 0.130 | 0.042 | 0.307 | 20.4 | 76.9 | 0.35 | 0.018 | 0.016 | 46.6 |
| 518px | 0.117 | 0.039 | 0.258 | 19.7 | 77.7 | 0.36 | 0.016 | 0.016 | 22.5 |



Input Pi3 W/o mono. prior **Ours**

Figure 6. Comparison on disparity quality on Pi3, our variant without monocular prior, and our full model.

**Ablation on sharpness depth.** Tab. 6b ablates the contribution of the monocular prior [77] and the gradient loss; Fig. 6 shows qualitative results with and without the prior.

**Ablation on LR-stream resolution.** We vary the LR stream resolution in Tab. 7. In general, increasing LR resolution slightly improves performance but significantly reduces the FPS.

## 5. Conclusion

We introduced DAGE, a dual-stream visual geometry transformer. A low-resolution stream efficiently estimates cameras and enforces cross-view consistency, while a high-resolution stream preserves sharp details; a lightweight adapter fuses them. This decouples resolution from sequence length, supporting 2K inputs and long videos at practical costs. Empirically, DAGE yields sharper pointmaps and outperforms prior video geometry methods. It matches the 3D reconstruction and pose accuracy of state-of-the-art models [74, 79] while running significantly faster.
**Limitations.** Performance can drop under extremely low overlap or rapid non-rigid motion; the HR path is memory-intensive at very high resolutions; and the current method does not recover dynamic motion.

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