
VGGT : Visual Geometry Grounded Transformer

 *Best award*

Paper Review

2025.09.04

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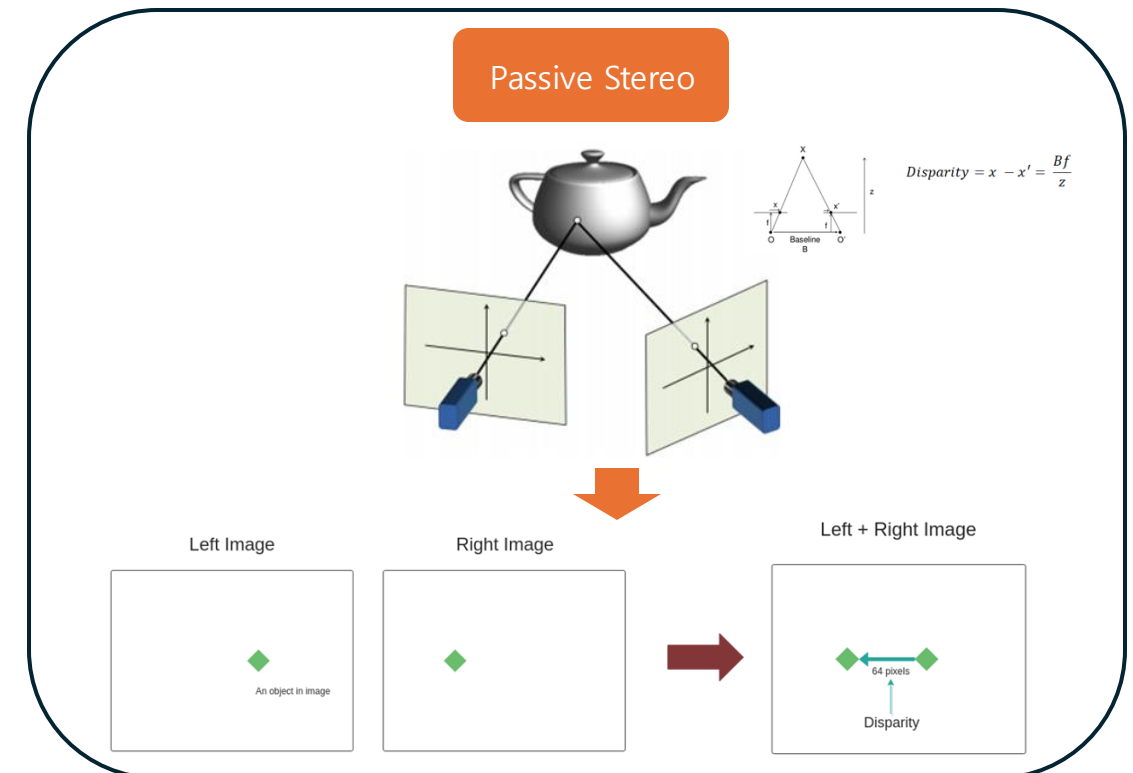
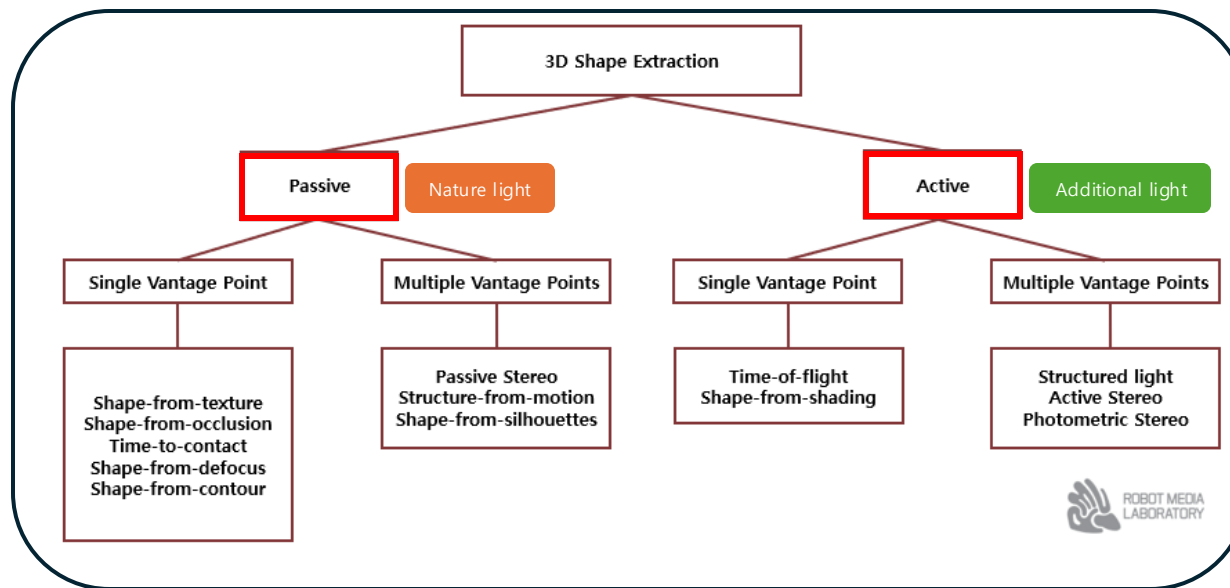
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Introduction

Background(1)

❖ 3D reconstruction

- The process of creating a 3D model of a target object or scene using 2D images or other data (eg. Laser scan)
- Robotics, Virtual Reality (VR), Autonomous Driving

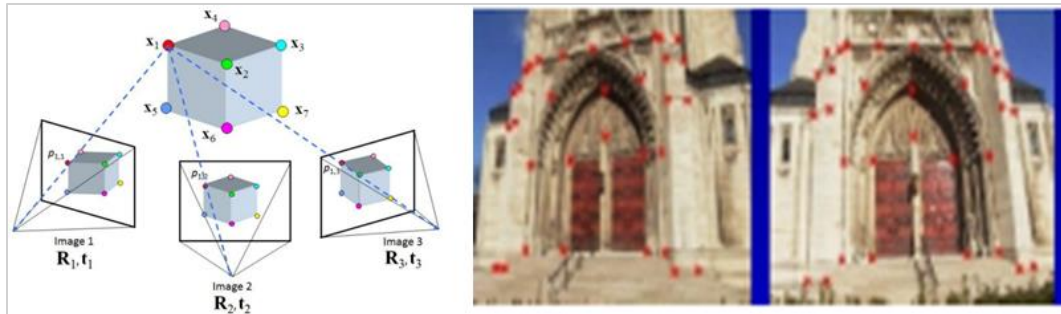


Introduction

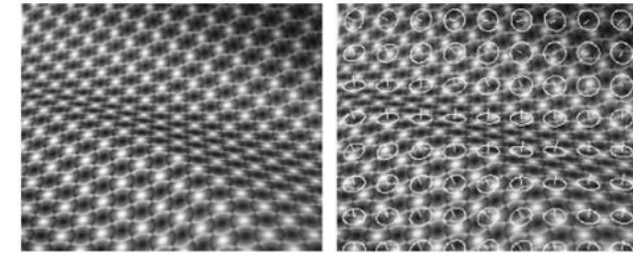
Background(1)

❖ 3D reconstruction – Passive

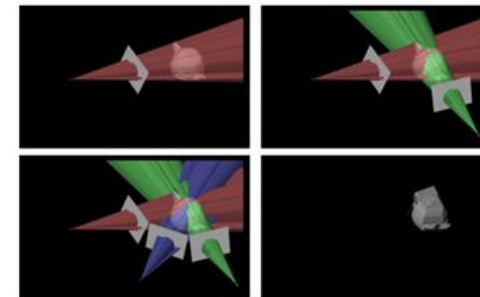
Structure-from-Motion(SFM)



Shape-from-Texture and Shape-from-Contour



Shape-from-Silhouettes



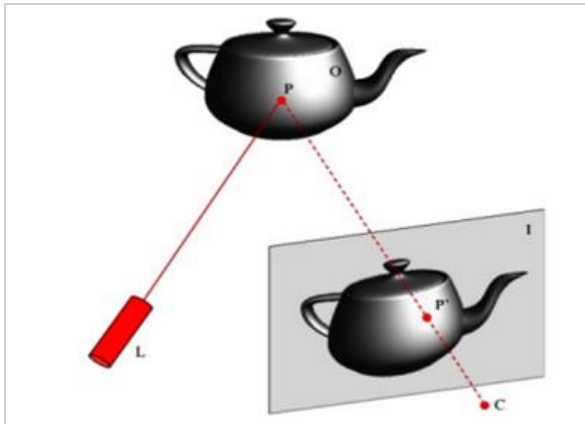
Introduction

Background(1)

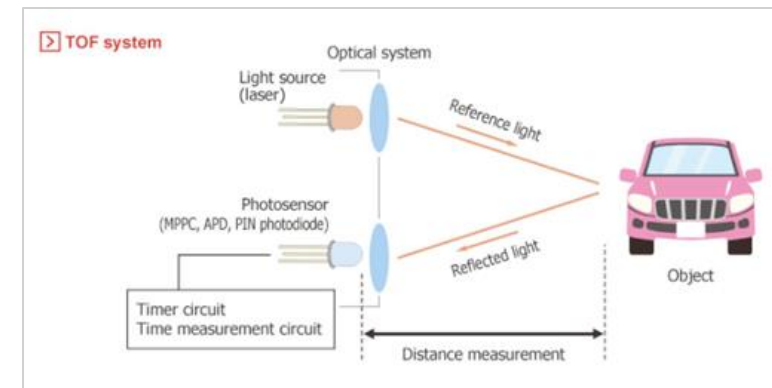
❖ 3D reconstruction – Active

- A technique of using additional light
- Difficult to collect data because of using other devices like lasers and make data
- Reliability is high due to low impact on surrounding environment

Active Stereo



Time-of-Flight(ToF)

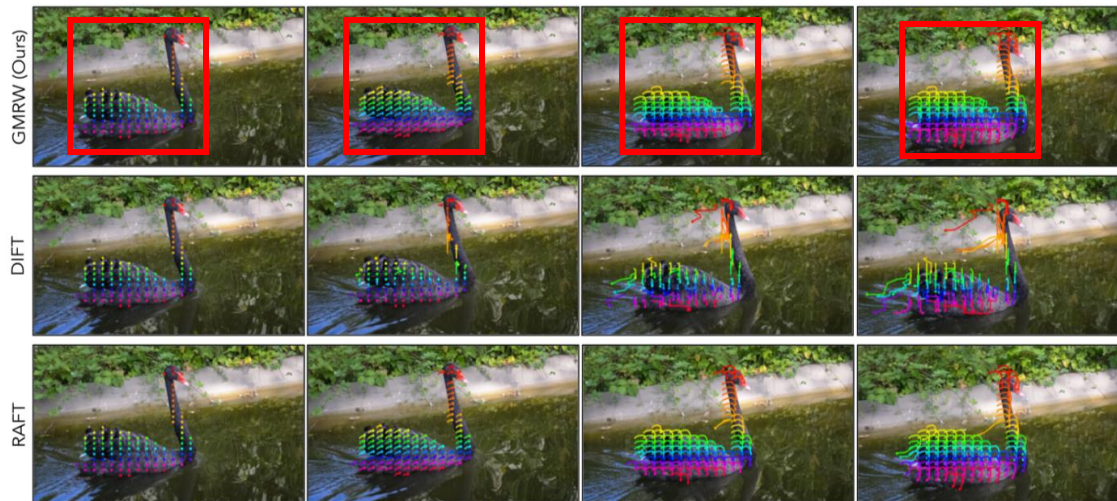


Introduction

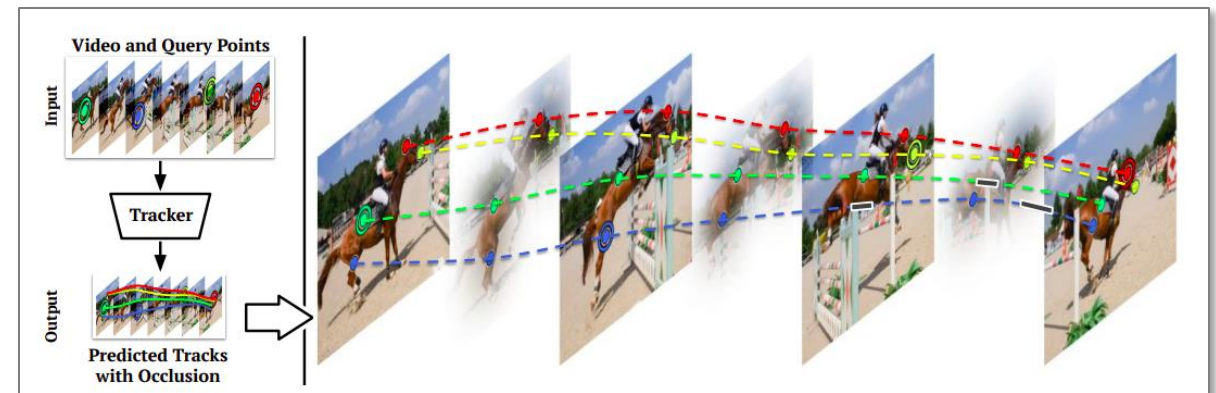
Background(2)

❖ Tracking-Any-Point

- Track points of interest throughout the video sequence, including dynamic movements
- Predict the 2D positions corresponding to these points in all different frames (Input video & 2D query points)



Time →

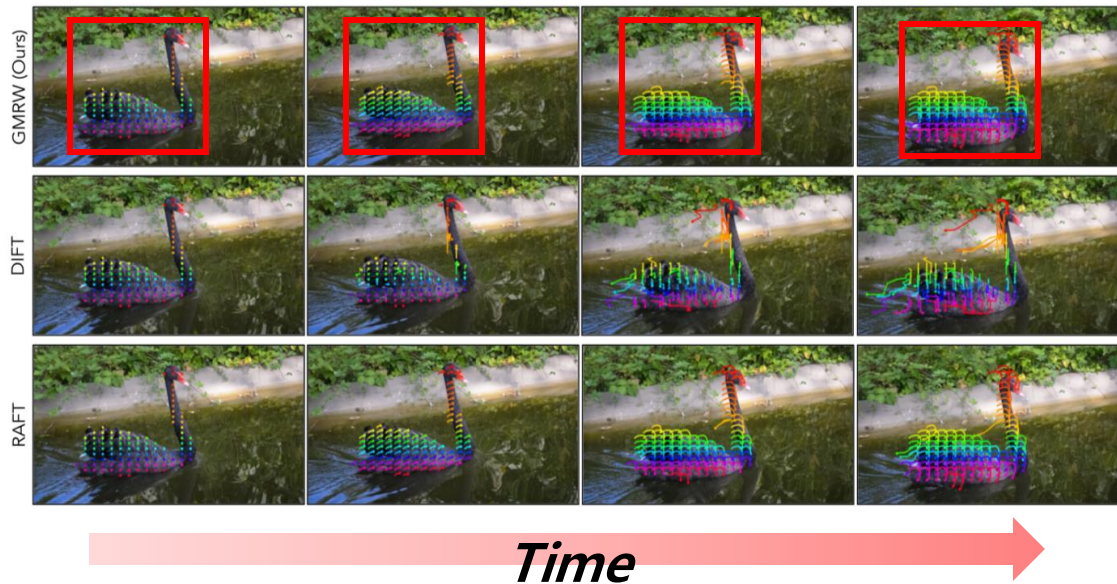


Introduction

Background(2)

❖ Tracking-Any-Point

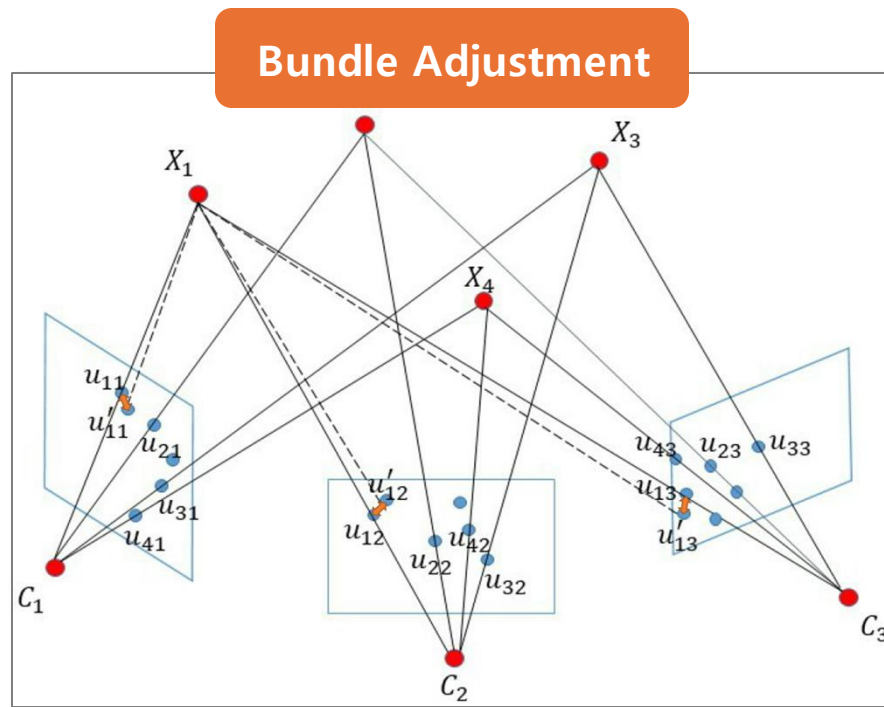
- Track points of interest throughout the video sequence, including dynamic movements
- Predict the 2D positions corresponding to these points in all different frames (Input video & 2D query points)



Purpose

❖ Limitation of prior works

- Increasing complexity and computational cost of iterative optimization (eg. Bundle Adjustment)
- Processing images in pairs → Reconfigure multiple images with post-processing



Purpose

❖ Limitation of prior works

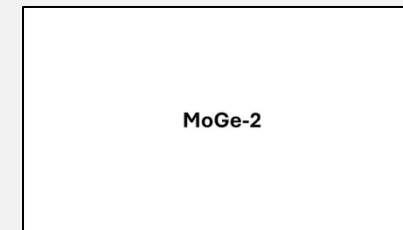
- All large scale 3D neural networks, but models each focused on a single 3D task
- Transformer based large scale foundation model



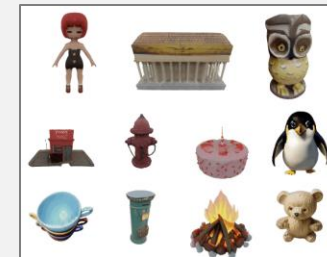
Depth Anything



MoGe-2

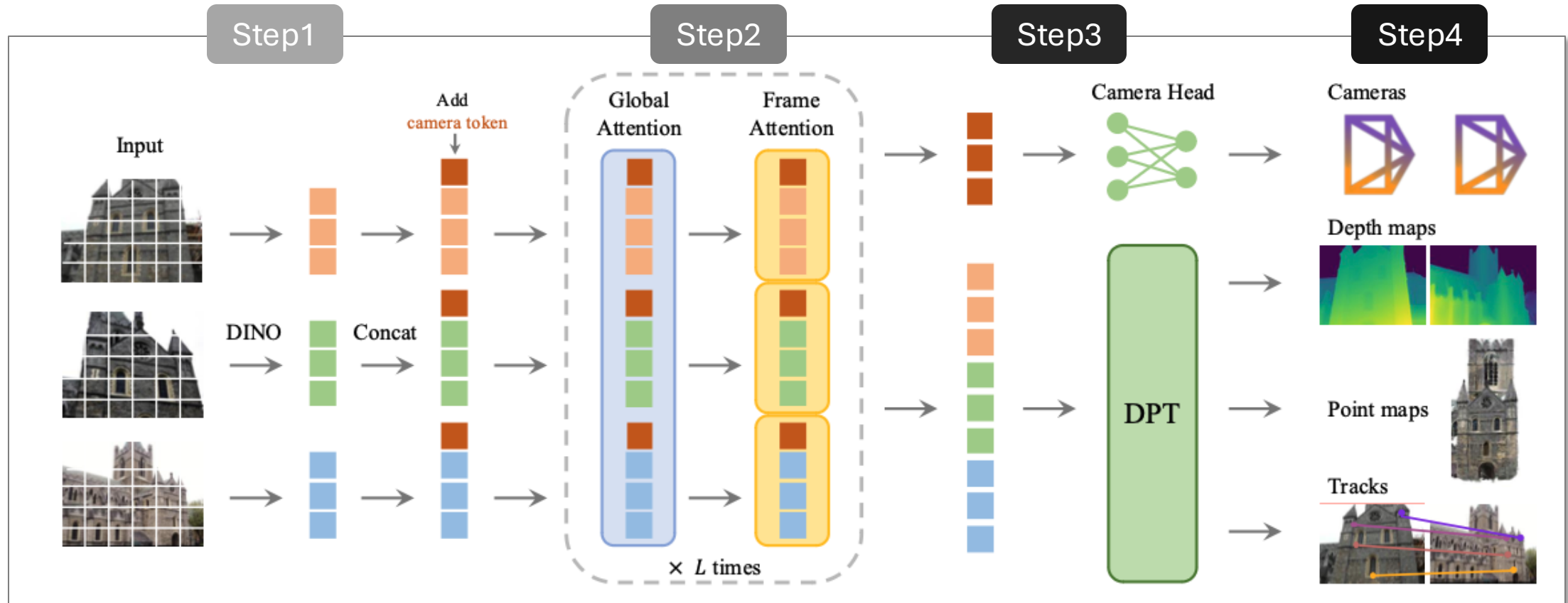


LRM



Method

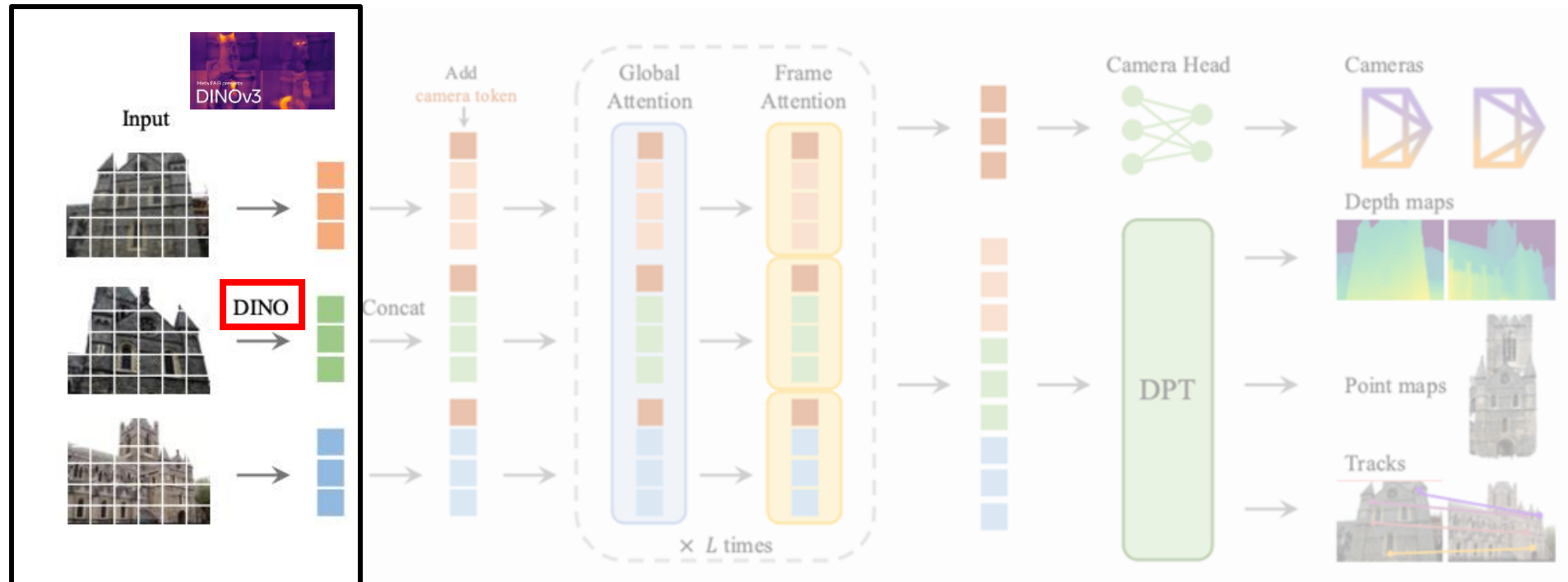
❖ Overall Architecture



Purpose

❖ Step1. – Input

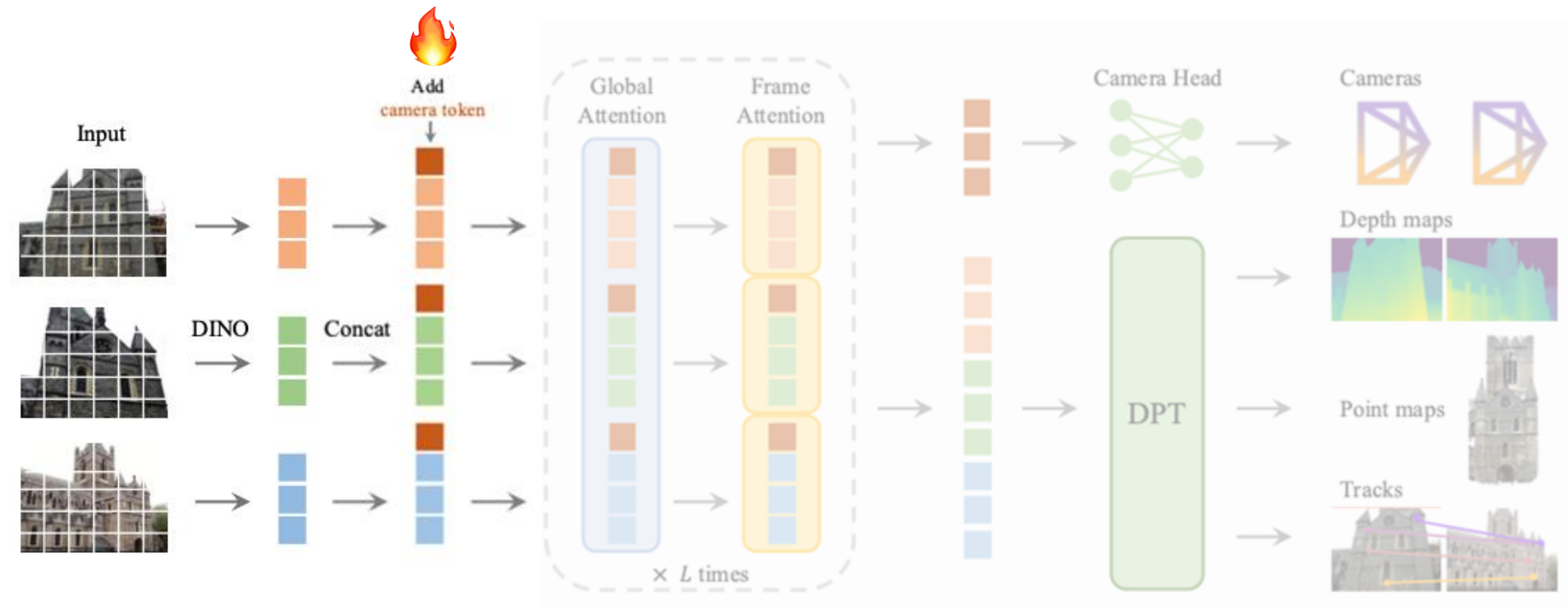
- Input: N RGB image sequences as inputs (can be entered in any order)
- Input images are converted to tokens through Pretrained DINO
- Add a camera token to each image for camera parameter prediction



Purpose

❖ Step1. – Input

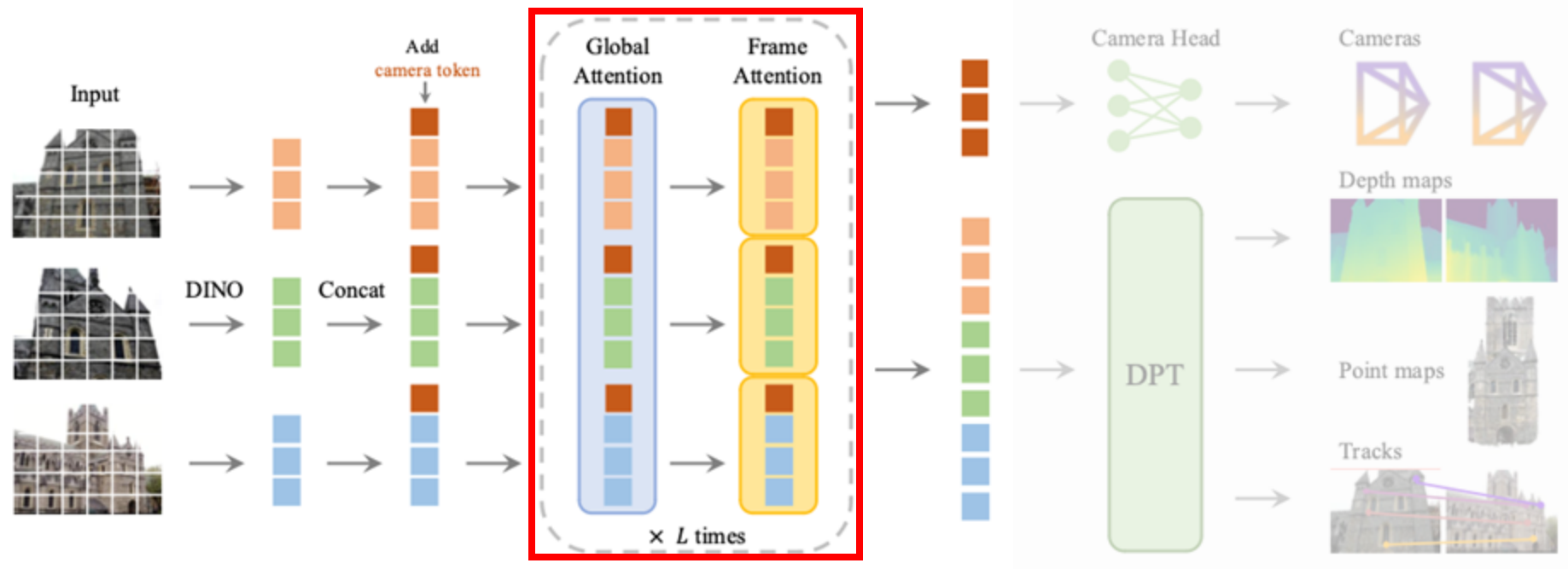
- Input: N RGB image sequences as inputs (can be entered in any order)
- Input images are converted to tokens through Pretrained DINO
- Add a camera token to each image for camera parameter prediction



Purpose

❖ Step2. – Alternating Attention(AA)

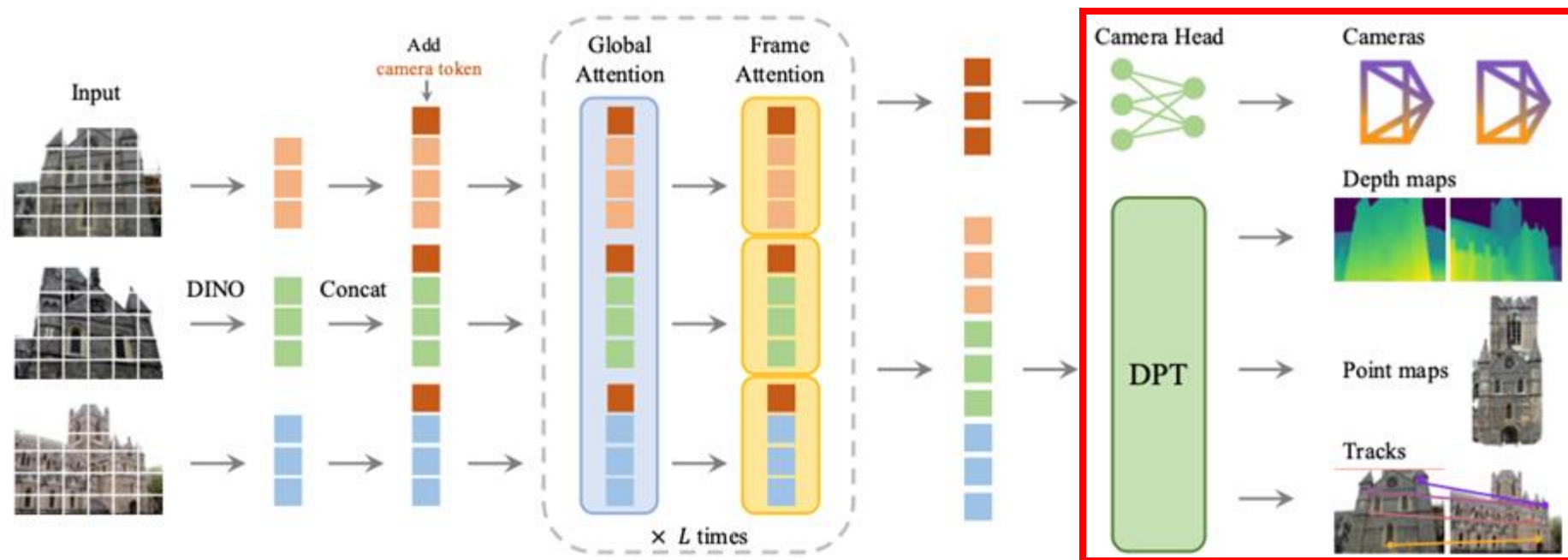
- Perform attention on all tokens in all frames
- Synthesizes information between images, and learn relationships between images



Purpose

❖ Step3. – Prediction

- Camera Head : Predict of the camera's internal/external parameters from the camera token
- DPT : Perform Dense Prediction, such as Depth Map, Point Map, etc. from image token



Purpose

❖ Training Losses

$$\mathcal{L} = \mathcal{L}_{\text{camera}} + \mathcal{L}_{\text{depth}} + \mathcal{L}_{\text{pmap}} + \lambda \mathcal{L}_{\text{track}}.$$

Camera Loss

$$\mathcal{L}_{\text{camera}} = \sum_{i=1}^N \|\hat{\mathbf{g}}_i - \mathbf{g}_i\|_{\epsilon}$$

Depth map Loss

$$\mathcal{L}_{\text{depth}} = \sum_{i=1}^N \|\Sigma_i^D \odot (\hat{D}_i - D_i)\| + \|\Sigma_i^D \odot (\nabla \hat{D}_i - \nabla D_i)\| - \alpha \log \Sigma_i^D$$

Point map loss

$$\mathcal{L}_{\text{pmap}} = \sum_{i=1}^N \|\Sigma_i^P \odot (\hat{P}_i - P_i)\| + \|\Sigma_i^P \odot (\nabla \hat{P}_i - \nabla P_i)\| - \alpha \log \Sigma_i^P$$

Tracking loss

$$\mathcal{L}_{\text{track}} = \sum_{j=1}^M \sum_{i=1}^N \|\mathbf{y}_{j,i} - \hat{\mathbf{y}}_{j,i}\|$$

Result

❖ Visualization of Point Map Estimation

- Point map visualization generated by the VGGT model
- VGGT works well in different kinds of scenes, such as buildings, indoor props, and outdoor environments
- Complex textures such as asphalt are also excellent



Result

❖ Camera Pose Estimation

- Red : Existing optimization-based method: longer than 10 seconds
- Blue : slightly run time improved model but still take a long time
- Green: Time has gotten a lot faster but AUC score is too low
- **Purple (Our model)** : Runtime is very fast. + Bundle adjustment slows down time but increases AUC score

Methods	Re10K (<i>unseen</i>) AUC@30 ↑	CO3Dv2 AUC@30 ↑	Time
Colmap+SPSG [92]	45.2	25.3	~ 15s
PixSfM [66]	49.4	30.1	> 20s
PoseDiff [124]	48.0	66.5	~ 7s
DUS3R [129]	67.7	76.7	~ 7s
MASt3R [62]	76.4	81.8	~ 9s
VGGsFM v2 [125]	78.9	83.4	~ 10s
MV-DUS3R [111] ‡	71.3	69.5	~ 0.6s
CUT3R [127] ‡	75.3	82.8	~ 0.6s
FLARE [156] ‡	78.8	83.3	~ 0.5s
Fast3R [141] ‡	72.7	82.5	~ 0.2s
Ours (Feed-Forward)	<u>85.3</u>	<u>88.2</u>	~ 0.2s
Ours (with BA)	93.5	91.8	~ 1.8s

Result

❖ Dense MVS Estimation

- 3D reconstruction task using multi view stereo images
- Competitive in performance with the latest MVS methods, even if you don't know the actual camera parameter.

Known GT camera	Method	Acc.↓	Comp.↓	Overall↓
✓	Gipuma [40]	0.283	0.873	0.578
✓	MVSNet [144]	0.396	0.527	0.462
✓	CIDER [139]	0.417	0.437	0.427
✓	PatchmatchNet [121]	0.427	0.377	0.417
✓	MASt3R [62]	0.403	0.344	0.374
✓	GeoMVSNet [157]	0.331	0.259	0.295
✗	DUS3R [129]	2.677	0.805	1.741
✗	Ours	0.389	0.374	0.382

Table 2. **Dense MVS Estimation on the DTU [51] Dataset.** Methods operating with known ground-truth camera are in the top part of the table, while the bottom part contains the methods that do not know the ground-truth camera.

Result

❖ Visualization of Rigid and Dynamic Point Tracking

- No matter input images sequence
- Dynamic: Follow the Keypoint's trajectory



Figure 5. **Visualization of Rigid and Dynamic Point Tracking.** Top: VGGT’s tracking module \mathcal{T} outputs keypoint tracks for an unordered set of input images depicting a static scene. Bottom: We finetune the backbone of VGGT to enhance a dynamic point tracker CoTracker [56], which processes sequential inputs.

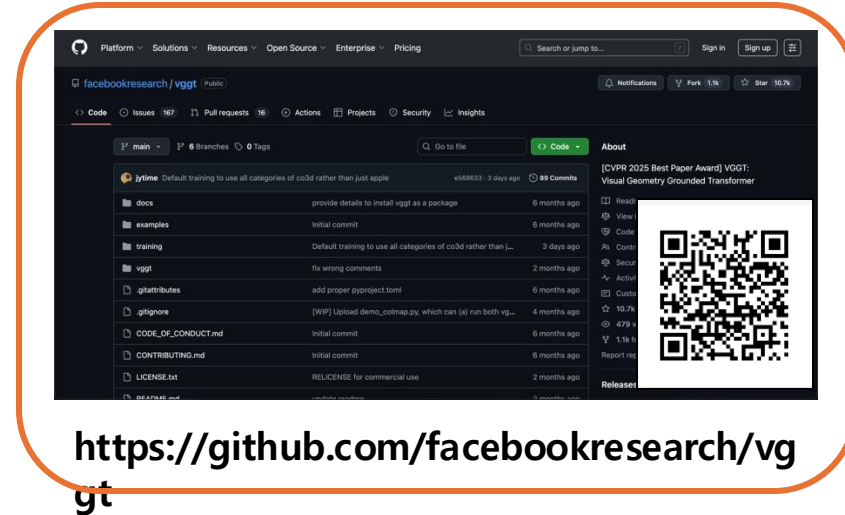
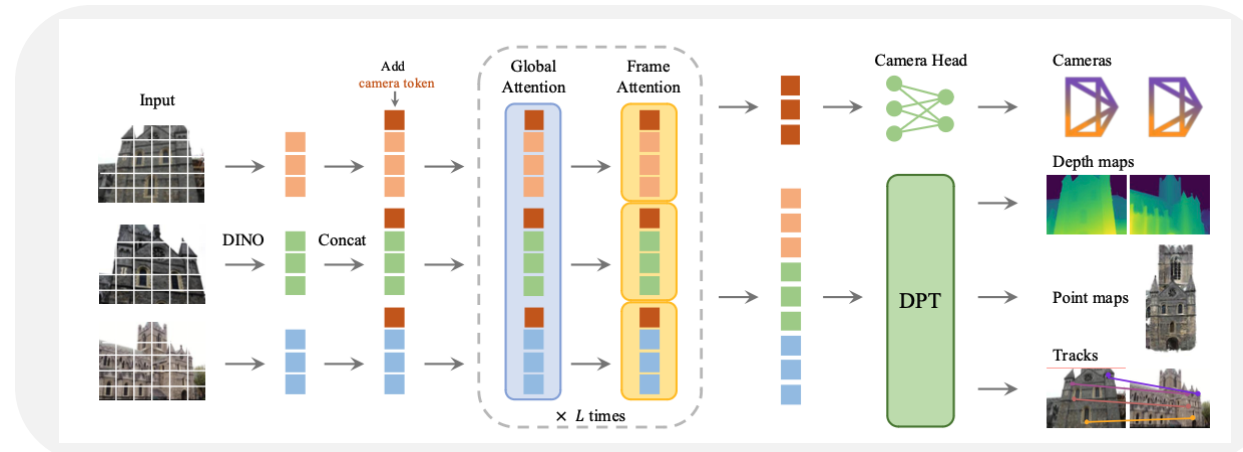
Conclusion

❖ Limitation

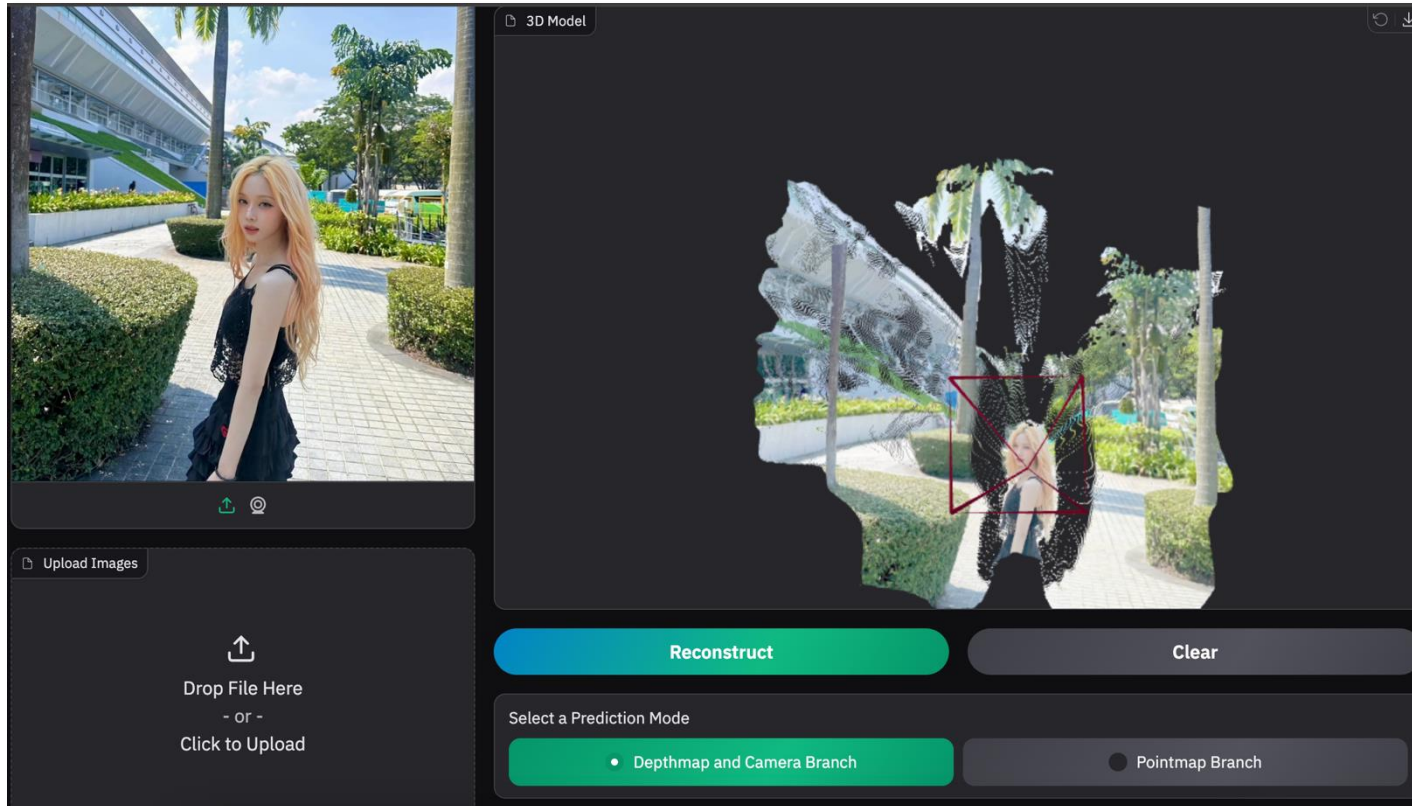
- Does not support fisheye or panoramic images
- Performance degrades at extreme input rotation
- It can handle minor non-rigid body movements, but fails in scenes with large variations

❖ Conclusion

- A feedforward neural network that can directly estimate all key 3D scene properties for hundreds of input views
- State-of-the-art performance in camera parameter estimation, multi-view depth estimation, dense point cloud reconstruction, and 3d point tracking



Code



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