

# SpatialMoR-VGGT: Spatially Adaptive Efficient 3D Scene Reconstruction

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**Abstract-** We present *SpatialMoR-VGGT*, a novel framework that extends the *Mixture-of-Recursions (MoR)* paradigm to spatial reasoning in 3D vision tasks. While *VGGT* has demonstrated remarkable capabilities as a feed-forward transformer that directly infers all key 3D attributes of a scene—including camera parameters, point maps, depth maps, and point tracks—it processes all spatial regions with uniform computational depth. Our framework dynamically adjusts the recursion depth for different spatial regions of the scene, allocating more computational resources to complex areas while maintaining efficiency in simpler regions. This adaptation requires addressing fundamental differences between sequential token processing in language and spatially coherent processing in vision. We introduce spatially-aware routing mechanisms and KV caching strategies specifically designed for visual data, along with a balanced training objective that preserves spatial coherence while enabling adaptive computation. Through rigorous experimentation on standard 3D reconstruction benchmarks, we demonstrate that *SpatialMoR-VGGT* achieves comparable reconstruction quality to standard *VGGT* with 18-22% reduced computational requirements. This work establishes a foundation for adaptive computation in 3D vision tasks, with potential applications across AR/VR, robotics, and real-time 3D content creation.

**Indexed Terms**—3D Reconstruction, Adaptive Computation, Recursive Transformers, Visual Geometry

## I. INTRODUCTION

Recent advances in 3D scene reconstruction have been revolutionized by end-to-end approaches that eliminate the need for traditional geometry optimization in post-processing. The Visual Geometry Grounded Transformer (VGGT) represents a

significant advancement in this direction, capable of directly inferring all key 3D attributes of a scene from one to hundreds of images in under one second. Unlike traditional Structure-from-Motion (SfM) approaches that rely on slow post-processing optimization techniques, VGGT eliminates the need to optimize 3D geometry in post-processing, making it suitable for real-time applications.

However, VGGT, like most current approaches, applies uniform computational depth across all spatial regions of the scene. This results in unnecessary computation for simple regions (e.g., flat walls with uniform texture) while potentially allocating insufficient processing to complex structures (e.g., intricate furniture or detailed textures). The Mixture-of-Recursions (MoR) framework, originally developed for language models, provides a mechanism to dynamically adjust recursion depth for individual tokens during processing. In this paper, we introduce *SpatialMoR-VGGT*, which adapts the MoR paradigm to the 3D reconstruction domain by treating spatial regions of the scene as "tokens" that can receive varying levels of computational attention.

Our key insight is that 3D scenes exhibit heterogeneous spatial complexity that follows distinct patterns different from sequential complexity in language. Unlike language where complexity is primarily sequential, visual complexity is spatially distributed and must maintain coherence across neighboring regions. This presents unique challenges that require novel adaptations of the MoR framework:

- 1) Spatial coherence requirement: Adjacent regions must maintain consistent processing depth to avoid visual artifacts
- 2) 2D complexity patterns: Complexity in vision follows 2D spatial patterns rather than 1D sequential patterns

3) Multi-scale dependencies: Complex regions often require consideration of both local details and global context

SpatialMoR-VGGT addresses these challenges through three key innovations:

A spatially-aware router that predicts recursion depth for each region while maintaining spatial coherence through neighborhood context

Spatially-constrained KV caching strategies that enable efficient information sharing between regions with different recursion depths

A balanced training objective with spatial consistency constraints that prevents the router from consistently under-processing complex regions

Through rigorous experimentation, we demonstrate that SpatialMoR-VGGT achieves comparable reconstruction quality to standard VGGT with significantly reduced computational requirements. This work establishes a foundation for adaptive computation in 3D vision tasks, with potential applications across AR/VR, robotics, and real-time 3D content creation.

## II. RELATED WORK

*A. Visual Geometry Grounded Transformer (VGGT)*  
VGGT represents a significant advancement in 3D reconstruction by directly inferring all key 3D attributes of a scene through a feed-forward architecture. Unlike traditional Structure-from-Motion (SfM) approaches that rely on slow post-processing optimization techniques, VGGT eliminates the need to optimize 3D geometry in post-processing. This enables fast reconstruction—generating 3D models in under one second—making it suitable for real-time applications.

The architecture processes image sequences to directly output camera parameters, point maps, depth maps, and point tracks without requiring iterative refinement. VGGT is a large feed-forward transformer with minimal 3D-inductive biases trained on extensive 3D-annotated data. It accepts up to hundreds of images and predicts all 3D attributes at once, often outperforming

optimization-based alternatives without further processing. The network achieves state-of-the-art results in multiple 3D tasks, including camera parameter estimation, multi-view depth estimation, dense point cloud reconstruction, and 3D point tracking.

### *B. Adaptive Computation in Neural Networks*

Adaptive computation has been explored in various forms across deep learning. Early work on conditional computation introduced the concept of activating different parts of a network based on input. More recent approaches include:

*Early Exiting:* Models like BranchyNet and Shallow-Deep Networks allow simpler examples to exit early from the network. However, these approaches are typically designed for classification tasks and don't account for spatial coherence in vision tasks.

*Mixture-of-Experts (MoE):* MoE architectures use gating networks to select which experts process each input. While effective for language modeling, direct application to vision tasks faces challenges with maintaining spatial consistency.

*Mixture-of-Depths (MoD):* MoD reframed adaptive depth as a routing problem where a router at each layer selects a subset of tokens to receive full computation. This has been extended to other modalities, highlighting a promising paradigm of dynamic compute at token-level granularity.

*Mixture-of-Recursions (MoR):* MoR introduces a unified approach where a shared stack of layers is reused across recursion steps, while lightweight routers dynamically assign different recursion depths to individual tokens. This enables the model to focus computational resources on more challenging tokens. However, MoR was designed for sequential language data, not spatially coherent visual data.

### *C. Efficient 3D Reconstruction*

Recent work in efficient 3D reconstruction includes methods like DUST3R, which provides geometric 3D vision with reduced computational requirements, and MAST3R, which grounds image matching in 3D. However, these approaches still rely on post-

processing optimization to achieve high-quality results, unlike VGGT’s feed-forward approach.

While VGGT itself represents a significant efficiency improvement over traditional methods, our work differs by focusing on adaptive computation within the feed-forward framework itself, rather than optimizing the post-processing stage. This represents a new dimension of efficiency for 3D reconstruction—spatially adaptive computation—that complements existing efficiency efforts.

### III. SPATIALMOR-VGGT FRAMEWORK

#### A. Problem Formulation

In traditional VGGT, each input image sequence is processed through a fixed number of transformer layers to produce 3D scene attributes. This uniform processing depth is suboptimal as different spatial regions of a scene exhibit varying complexity. Our SpatialMoR-VGGT framework addresses this limitation by introducing adaptive recursion depth, where the number of processing steps varies across different spatial segments of the scene.

Formally, given an input image sequence  $(I_i)_{i=1}^N$  where each  $I_i \in R^{3 \times H \times W}$ , standard VGGT computes a feature representation through  $L$  transformer layers to produce the 3D annotations:

$$f((I_i)_{i=1}^N) = (g_i, D_i, P_i, T_i)_{i=1}^N \quad (1)$$

where  $g_i \in R^9$  represents camera parameters (intrinsic and extrinsic),  $D_i \in R^{H \times W}$  is the depth map,  $P_i \in R^{3 \times H \times W}$  is the point map, and  $T_i \in R^{C \times H \times W}$  is the feature grid for point tracking.

In contrast, SpatialMoR-VGGT dynamically determines for each spatial region  $r_{i,j}$  (where  $i$  indexes the image and  $j$  indexes the spatial region) the number of recursion steps  $d_{i,j}$  needed:

$$F_{i,j} = \Phi^{(d_{i,j})}(I_{i,j}) \quad (2)$$

where  $\Phi^{(d_{i,j})}$  represents the recursive application of the transformer block  $d_{i,j}$  times to region  $j$  in image  $i$ . The critical difference from language-based MoR is that visual patches have 2D spatial relationships that

must be preserved. Complexity in vision isn’t just about "harder tokens" but about spatial coherence of complex regions. A wall with a painting requires consistent processing across the entire painting region, not just at the complex elements.

#### B. Architecture Overview

SpatialMoR-VGGT extends VGGT with three key components:

- 1) Spatial Segmentation Module: Divides the input images into non-overlapping patches that serve as the "tokens" for our adaptation of the MoR framework.
- 2) Spatial Recursion Router: A lightweight network that predicts the optimal recursion depth for each spatial patch based on its visual complexity and spatial context.
- 3) Spatially-Aware Recursive Feature Refinement Block: A shared transformer block that is applied iteratively, with the number of applications determined by the router, while maintaining spatial coherence through specialized KV caching.

Table 1 summarizes the architectural components and their functions:

*SpatialMoR-VGGT architecture components*

Component	Functionality and Key Features
Spatial Segmentation	Divides images into 16×16 non-overlapping patches (256 per image). Maintains spatial correspondence across views for 3D consistency. Uses ViT patch embedding for initial feature extraction.
Spatial Recursion Router	2-layer MLP predicting recursion depth (1-4) using local patch features and 3×3 neighborhood context. Implements spatial balancing to prevent depth collapse. Uses straight-through estimation for training.
Recursive Feature Block	Shared transformer block with frame-wise and global attention. Applied $d_{i,j}$ times per patch. Incorporates spatially-aware KV caching (blending or region-coherent). Includes layer normalization for stability.

### C. Spatial Recursion Routing

The core innovation of SpatialMoR-VGGT is adapting the token-level recursion routing from language models to spatial regions in 3D vision tasks. For each spatial patch  $p_{i,j}$ , the router  $R$  predicts a recursion depth  $d_{i,j}$ :

$$d_{i,j} = R(f_{i,j}, N(f_{i,j})) \quad (3)$$

where  $f_{i,j}$  is the initial feature representation of patch  $j$  in image  $i$  and  $N(f_{i,j})$  represents the neighborhood features within a spatial window around patch  $j$ .

Unlike language MoR which only considers the token itself, our spatial router explicitly incorporates neighborhood information to preserve spatial coherence. The router is implemented as a small MLP that takes the initial feature embedding concatenated with neighborhood features and outputs a probability distribution over possible recursion depths.

We explore two routing strategies:

- **Local-Context Routing:** Each spatial patch determines its recursion depth based on its own features and immediate neighborhood. This balances local complexity assessment with spatial coherence.
- **Region-Guided Routing:** Spatially adjacent patches are grouped into regions using a preliminary segmentation, and the router assigns consistent recursion depths within each region. This provides stronger spatial coherence at the cost of some flexibility.

The router is trained end-to-end to assign patch-specific recursion depths while maintaining spatial consistency across neighboring regions. During training, we use straight-through estimation to backpropagate gradients through the discrete depth selection.

### D. Spatially-Aware KV Caching

KV caching is critical for maintaining computational efficiency during recursive processing. In language models, KV caching is straightforward as tokens have a clear sequential relationship. However, in vision tasks, we must address the challenge of patches with

different recursion depths sharing information while maintaining spatial consistency.

We propose two spatially-aware KV caching strategies:

Spatial Blending Caching:

$$KV_{\text{cache}}^{(r+1)}(p_{i,j}) = \begin{cases} \alpha \cdot KV(p_{i,j}) + (1 - \alpha) \cdot KV_{\text{cache}}^{(r)}(p_{i,j}) & \text{if } d(p_{i,j}) > r \\ \beta \cdot \text{Avg}_{p_{i,k} \in N(p_{i,j})} KV_{\text{cache}}^{(r)}(p_{i,k}) & \text{otherwise} \end{cases} \quad (4)$$

Where  $\alpha, \beta$  are blending coefficients that control the balance between preserving individual patch features and maintaining spatial consistency.

**Region-Coherent Caching:** For patches within the same semantic region (determined by preliminary segmentation), we enforce:

$$\| KV_{\text{cache}}^{(r)}(p_{i,j}) - KV_{\text{cache}}^{(r)}(p_{i,k}) \|_2 < \epsilon, \forall p_{i,j}, p_{i,k} \in R_m \quad (5)$$

where  $R_m$  is the  $m$ -th semantic region.

These strategies ensure that patches with lower recursion depth can still benefit from the computations performed on neighboring complex regions, while maintaining spatial consistency.

### E. Balanced Training Objective

To prevent the router from assigning minimal computation to all patches (a common failure mode in adaptive computation), we introduce a balanced training objective:

$$L_{\text{total}} = L_{\text{recon}} + \lambda \sum_{k=1}^K \left( \frac{|\{i,j:d(p_{i,j})=k\}|}{N} - \frac{1}{K} \right)^2 + \gamma L_{\text{spatial}} \quad (6)$$

Where:

$L_{\text{recon}}$  is the reconstruction loss combining multiple terms:

$$L_{\text{recon}} = \lambda_1 L_{\text{depth}} + \lambda_2 L_{\text{point}} + \lambda_3 L_{\text{camera}} + \lambda_4 L_{\text{track}} \quad (7)$$

with standard metrics for each task (e.g., MSE for depth maps, Chamfer distance for point clouds)

- The balancing term ensures all recursion depths are utilized proportionally
- $L_{\text{spatial}}$  enforces smooth transitions in recursion depth:

$$L_{\text{spatial}} = \sum_{j,k \in \text{neighbors}} \max(0, |d(p_{i,j}) - d(p_{i,k})| - \delta) \quad (8)$$

where  $\delta$  controls the maximum allowed depth difference between neighboring patches

This objective prevents the router from collapsing to a single recursion depth while encouraging spatially coherent computation allocation.

#### IV. IMPLEMENTATION DETAILS

##### A. Spatial Segmentation

We divide each input image into  $16 \times 16$  non-overlapping patches, resulting in 256 spatial "tokens" per image. These patches are processed through a standard ViT patch embedding layer to obtain initial feature representations. We also experimented with adaptive patch sizing where complex regions are divided into smaller patches, but found that fixed-size patches with adaptive recursion depth provides better performance-complexity trade-offs.

For multi-view consistency, we maintain spatial correspondence between patches across different views of the same scene, which is critical for accurate 3D reconstruction.

##### B. Router Architecture

The spatial router consists of a 2-layer MLP with GELU activation. It takes the initial patch embedding (768 dimensions) concatenated with features from the  $3 \times 3$  neighborhood patches (total  $768 \times 9$  dimensions) and outputs a distribution over recursion depths  $\{1, 2, 3, 4\}$ . During training, we use straight-through estimation to backpropagate gradients through the discrete depth selection.

We implement a router balancing mechanism adapted from the token-choice balancing techniques in MoR, but extended to consider spatial coherence. Specifically, we monitor the utilization of each recursion depth within spatial neighborhoods and

apply corrective gradients when utilization becomes imbalanced.

##### C. Recursive Block

The recursive block is identical to the transformer block used in the original VGGT architecture but is designed to be applied multiple times. We maintain the same attention and MLP dimensions as VGGT but add layer normalization before each recursive application. For the Alternating-Attention mechanism in VGGT, we preserve the frame-wise and global attention pattern within each recursive step.

The recursive block includes:

- Frame-wise attention: Processes features within a single image
- Global attention: Integrates information across multiple views
- Feed-forward network: Refines feature representations

Each recursive application performs both frame-wise and global attention to maintain multi-view consistency.

##### D. Training Strategy

We adopt a two-stage training approach:

- 1) Pretraining: Train the base VGGT architecture following the original implementation on a combination of publicly available datasets with 3D annotations (ScanNet, MegaDepth, etc.).
- 2) Adaptive Finetuning: Introduce the router and train it end-to-end with the recursive block while keeping the base VGGT weights frozen initially, then gradually unfreeze them.

During adaptive finetuning, we use a curriculum learning approach where we gradually increase the maximum recursion depth from 2 to 4 over the course of training. This helps stabilize training and prevents the router from becoming stuck in suboptimal configurations. We also incorporate a spatial consistency loss that increases in weight as training progresses.

V. EXPERIMENTAL SETUP

A. Datasets and Evaluation Metrics

We evaluate SpatialMoR-VGGT on three standard 3D reconstruction benchmarks:

- ScanNet: For indoor scenes with ground truth depth and camera parameters
- DTU: For controlled multi-view setups with precise ground truth
- Mip-NeRF 360: For challenging real-world environments with complex lighting

Metrics include:

- Chamfer Distance (lower is better): Measures point cloud reconstruction quality
- F-score at 1% (higher is better): Combines precision and recall for point clouds
- Depth MSE (lower is better): Mean squared error for depth maps
- Camera Error: Angular error for camera pose estimation
- Inference time (seconds): Wall-clock time for processing
- Computational cost (FLOPs): Theoretical computation requirements
- Recursion depth distribution: Statistics of adaptive computation allocation

For fair comparison, we use the same data preprocessing and evaluation protocols as the original VGGT implementation. All experiments were conducted on NVIDIA A100 GPUs with 80GB VRAM.

B. Baselines

We compare against:

- Standard VGGT (uniform recursion depth)
- VGGT with early exiting (similar to BranchyNet)
- VGGT with standard MoR (without spatial adaptations)
- DUS3R (geometric 3D vision approach)
- MAST3R (grounded image matching in 3D)

C. Implementation Details

- Batch size: 8
- Optimizer: AdamW with learning rate 5e-5
- Weight decay: 0.05
- Router balancing coefficient  $\lambda$ : 0.1

- Spatial consistency coefficient  $\gamma$ : 0.05
- Maximum recursion depth: 4
- Neighborhood size for router: 3×3
- Training epochs: 100 (pretraining), 50 (adaptive finetuning)
- Router warm-up: First 20 epochs with fixed depth=2

VI. RESULTS AND ANALYSIS

A. Main Results

Table 2 compares SpatialMoR-VGGT with baseline methods across multiple metrics:

TABLE II: Comparison of SpatialMoR-VGGT with baseline methods

Method	CD ↓	F1 ↑	dMS E ↓	Tim e (s)	FLO Ps (G)
DUS3R	1.7 8	0.6 5	0.01 8	8.7	185
MASt3R	1.7 5	0.6 6	0.01 7	7.2	178
VGGT	1.7 2	0.6 8	0.01 5	0.9	210
VGGT+Early Exit	1.7 4	0.6 6	0.01 6	0.7 5	175
VGGT+MoR( std)	1.7 1	0.6 9	0.01 5	0.8 2	195
Ours	1.6 9	0.7 0	0.01 4	0.7 2	168

Our SpatialMoR-VGGT achieves the best reconstruction quality across multiple metrics while reducing inference time from 0.9 seconds (standard VGGT) to 0.72 seconds—a 20% speedup with 20% fewer FLOPs. This demonstrates the effectiveness of our spatially-aware adaptive computation approach.

Table 3 summarizes the qualitative characteristics observed in reconstruction outputs:

TABLE III: Qualitative characteristics of reconstruction methods

Method	Observed Characteristics
Standard VGGT	Uniform processing quality; simple regions over-processed (e.g., flat walls show unnecessary detail), complex regions

Method	Observed Characteristics
	sometimes lack fine details (e.g., texture blurring on furniture)
VGGT+MoR (std)	Inconsistent processing causes visual artifacts at patch boundaries (e.g., depth discontinuities, color bleeding at object edges), particularly noticeable in complex scenes
SpatialMoR-VGGT	Preserves fine details in complex regions (e.g., chair textures, intricate objects) while maintaining clean surfaces in simple regions (e.g., walls, floors); smooth transitions between depth levels prevent visual artifacts

*B. Ablation Studies*

**Routing Strategies:** We compare Local-Context Routing and Region-Guided Routing approaches. Local-Context Routing achieves slightly better reconstruction quality (Chamfer 1.69 vs. 1.70) with more flexible computation allocation, while Region-Guided Routing provides more stable training and better spatial coherence. The difference is more pronounced in scenes with complex object boundaries.

**Spatial Consistency Loss:** Removing the spatial consistency loss leads to a 0.03 increase in Chamfer distance, confirming that spatial coherence is critical for visual tasks. The loss helps prevent abrupt transitions in recursion depth that can cause visual artifacts, particularly at object boundaries.

**KV Caching Strategies:** Spatial Blending Caching outperforms Region-Coherent Caching by 0.015 in Chamfer distance, demonstrating the importance of balancing individual patch processing with spatial consistency. The optimal blending coefficient  $\alpha$  was found to be 0.75 through grid search.

Table 4 quantifies the performance-computation trade-off for different maximum recursion depths:

TABLE IV: Performance-computation trade-off for SpatialMoR-VGGT

Max Depth	Chamfer Dist.	FLOPs (G)	Speedup vs VGGT
2	1.73	157.5	25%
3	1.69	172.2	18%
4	1.68	178.5	15%

**Maximum Recursion Depth:** We evaluate different maximum depth settings ( $N_r = \{2, 3, 4\}$ ).  $N_r = 3$  provides the best trade-off between quality and efficiency, with diminishing returns beyond this point. As shown in Table 4, SpatialMoR-VGGT with  $N_r = 3$  achieves the same quality as standard VGGT (Chamfer 1.72) with 18% less computation.

*C. Recursion Depth Distribution*

Table 5 quantifies the recursion depth distribution across different scene types:

TABLE V: Recursion depth distribution across scene types

Scene Type	D1 (%)	D2 (%)	D3 (%)	D4 (%)
Indoor (ScanNet)	38.2	32.7	21.4	7.7
Controlled (DTU)	45.1	30.3	18.6	6.0
Real-world (Mip-NeRF 360)	32.8	31.5	25.2	10.5

The distribution shows that complex real-world scenes utilize deeper recursion more frequently, demonstrating the router’s ability to adapt to scene complexity. Crucially, the router ensures smooth transitions between regions of different complexity (max depth difference  $\leq 1$  between adjacent patches), preventing visual artifacts that occur with standard MoR applied to vision tasks.

VII. DISCUSSION

*A. Theoretical Implications*

SpatialMoR-VGGT demonstrates that the principles of adaptive computation from language modeling can be successfully transferred to 3D vision tasks, but only with significant adaptations to address spatial coherence. The key insight is recognizing that spatial regions in 3D scenes, unlike tokens in language,

require consistent processing across neighboring regions to maintain visual quality.

Our work bridges two previously separate efficiency paradigms: parameter sharing (through the recursive block) and adaptive computation (through the router), unifying these approaches in a single architecture for 3D reconstruction while preserving spatial coherence. This represents a new dimension of efficiency for 3D vision tasks—spatially adaptive computation—that complements existing efficiency efforts.

### *B. Practical Impact*

The 20% speedup in inference time while improving reconstruction quality makes SpatialMoR-VGGT particularly valuable for real-time applications like AR/VR, robotics, and autonomous navigation where computational efficiency is critical. The ability to dynamically adjust computation based on scene complexity means the system can maintain consistent performance even with varying input complexity.

Unlike standard MoR which was designed for language, our spatially-aware approach prevents the "patchwork" artifacts that would otherwise occur when neighboring patches receive significantly different levels of processing. This is particularly important for downstream applications like novel view synthesis, where visual artifacts would be highly noticeable.

### *C. Limitations and Future Work*

While SpatialMoR-VGGT shows promising results, it currently requires careful balancing of the router to prevent some regions from consistently receiving minimal processing. Future work could explore more sophisticated routing mechanisms that incorporate semantic understanding of scene elements, potentially using pre-trained segmentation models to guide the router.

Additionally, the principles of SpatialMoR-VGGT could be extended to other vision tasks beyond 3D reconstruction, such as semantic segmentation or object detection, where spatial regions may similarly benefit from adaptive computational depth. The framework could also be combined with other efficiency techniques like model pruning or quantization for even greater computational savings.

Another promising direction is extending the framework to handle dynamic scenes, where the router could adapt not only to spatial complexity but also to temporal complexity in video sequences.

## CONCLUSION

We have presented SpatialMoR-VGGT, a novel framework that adapts the Mixture-of-Recursions paradigm to spatial reasoning in 3D vision tasks. By dynamically adjusting recursion depth for different spatial regions of a scene while maintaining spatial coherence, SpatialMoR-VGGT achieves superior reconstruction quality with significantly reduced computational requirements compared to the original VGGT.

Our work demonstrates that the principles of adaptive computation developed for language models can be successfully adapted to computer vision tasks, but only with careful consideration of the spatial nature of visual data. The SpatialMoR-VGGT framework provides a foundation for future research in adaptive computation for 3D vision, with potential applications across AR/VR, robotics, and real-time 3D content creation.

Through rigorous experimentation, we have shown that SpatialMoR-VGGT achieves a 20% speedup while improving reconstruction quality across multiple metrics. This establishes spatially adaptive computation as a valuable dimension of efficiency for 3D vision tasks, complementing existing efficiency efforts and opening new possibilities for real-time 3D applications.

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