Enhanced 3D Gaussian Splatting for Object Removal: Perceptual Losses and Adaptive Depth Confidence Weighting

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Abstract

This paper presents enhancements to GScream after studying the paper "Learning 3D Geometry and Feature Consistent Gaussian Splatting for Object Removal" by Wang et al., a state-of-the-art method for 3D object removal using Gaussian Splatting. I reproduce the original implementation and introduce two novel contributions to address its limitations. First, I implement a multi-scale perceptual loss using VGG16 features and a gradient domain consistency loss to improve texture fidelity and reduce boundary artifacts. Second, I introduce an adaptive depth confidence weighting technique that automatically identifies unreliable depth regions and reduces their influence during training, resulting in improved geometry reconstruction. My quantitative evaluation demonstrates measurable improvements over the original method, with each novelty providing enhancements in PSNR (+0.6-0.7%), SSIM (up to +2.1% in masked regions), and LPIPS (up to -3.0%), while requiring minimal computational overhead. These improvements are most pronounced in the removed object regions and at object boundaries. The proposed techniques represent practical improvements to 3D Gaussian Splatting-based object removal, particularly for challenging scenes with complex boundaries and textures.

1 Introduction

Object removal from 3D scenes is a challenging task that requires seamless filling of the removed region while maintaining both geometric and photometric consistency. The recent introduction of 3D Gaussian Splatting (3DGS) [1] has enabled high-quality novel view synthesis with real-time rendering capabilities, making it suitable for interactive 3D applications. GScream [2] extends 3DGS specifically for object removal by incorporating monocular depth estimation and cross-attention feature propagation.

Despite these advances, GScream exhibits several limitations:

- **Boundary artifacts** and texture inconsistencies, particularly visible from novel viewpoints
- **Unreliable depth supervision**, especially at object boundaries where depth estimation is inherently challenging
- **Limited perceptual quality**, as basic L1 and SSIM losses fail to capture semantic coherence

In this work, I successfully reproduce the GScream approach and propose two novel enhancements to address these limitations:

1. **Perceptual and Gradient Domain Losses**: I implement a multi-scale perceptual loss based on VGG16 features and a gradient domain consistency loss to improve texture quality and reduce boundary artifacts.
2. **Adaptive Depth Confidence Weighting**: I introduce a technique that automatically identifies unreliable depth regions (particularly edges and discontinuities) and adaptively reduces their influence in the loss function.

My contributions result in measurable improvements in object removal quality, particularly at object boundaries and in maintaining consistent textures across novel viewpoints. Each enhancement requires minimal computational overhead while providing targeted improvements to specific aspects of the reconstruction.

2 Related Work

2.1 3D Gaussian Splatting

3D Gaussian Splatting [1] represents scenes using explicit 3D Gaussians, enabling high-quality, real-time novel view synthesis. Scaffold-GS [3] further optimizes this representation by organizing Gaussians around anchor points. GScream [2] adapts 3DGS specifically for object removal by leveraging monocular depth guidance and cross-attention for feature regularization.

2.2 Perceptual Losses

Perceptual losses using deep network features have become instrumental in image generation tasks. Johnson et al. [4] pioneered the use of VGG features for style transfer and super-resolution. Zhang et al. [5] demonstrated that learned perceptual image patch similarity (LPIPS) metrics correlate better with human perception than traditional metrics.

2.3 Depth Confidence Estimation

Estimating confidence in depth maps has been explored in various contexts. Xian et al. [6] introduced structure-guided ranking loss for depth estimation with uncertainty prediction. Casser et al. [7] proposed using uncertainty estimation for self-supervised depth learning. These approaches highlight the importance of modeling depth uncertainty, particularly at object boundaries.

2.4 Object Removal

Object removal from images and videos has been extensively studied in computer vision. Traditional methods rely on image inpainting techniques, such as Poisson image editing [8] and exemplar-based inpainting [12]. Recent approaches leverage deep learning for object removal, including neural radiance fields (NeRFs) [10, 11] and 3D Gaussian Splatting [2].

2.5 Neural Radiance Fields

NeRFs have revolutionized the field of 3D scene representation and rendering. Recent works have explored various aspects of NeRFs, including object removal [17], segmentation [13], and editing [15]. These advancements have paved the way for more sophisticated 3D scene understanding and manipulation techniques.

3 Methodology

I reproduce the GScream architecture for 3D object removal and implement two novel enhancements: perceptual and gradient domain losses, and adaptive depth confidence weighting.

3.1 GScream Reproduction

GScream builds upon 3D Gaussian Splatting, adapting it for object removal by:

1. **Initialization**: Starting with sparse 3D Gaussians from SfM point clouds
2. **Feature Bank**: Constructing a feature bank from visible regions in reference views
3. **Cross-Attention Mechanism**: Using a cross-attention mechanism to transfer features from the feature bank to fill in removed object regions
4. **Depth Constraints**: Incorporating monocular depth estimates to maintain geometric consistency

The core idea behind GScream is to leverage both 3D geometric information and 2D feature representations to achieve seamless object removal. The model uses a two-stage approach:

- **Stage 1**: Optimize the 3D Gaussians to match the visible parts of the scene (excluding the object to be removed)
- **Stage 2**: Incorporate cross-attention to fill in the removed object regions with features sampled from visible areas

The cross-attention mechanism in GScream is particularly innovative. It operates by:

1. Extracting features from visible regions in reference views
2. Storing these features in a feature bank
3. Computing attention weights between features in removed regions and those in the feature bank
4. Using these weights to fill in the removed regions with appropriate features

The loss function in the original GScream combines RGB and depth terms:

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{depth} \tag{1}$$

where $\mathcal{L}_{color}$ combines L1 and SSIM losses, and $\mathcal{L}_{depth}$ is an L1 loss between aligned predicted and ground truth depth maps.

In my reproduction, I carefully followed the implementation details described in the original paper, ensuring that all components—particularly the cross-attention mechanism and depth integration—were correctly implemented. I verified my reproduction by comparing the results with those reported in the original paper, achieving comparable performance metrics.

3.2 Novelty 1: Perceptual and Gradient Domain Losses

To improve texture fidelity and reduce boundary artifacts, I introduce a perceptual loss based on VGG16 features and a gradient domain consistency loss.

3.2.1 Motivation and Theoretical Background

Traditional pixel-wise losses like L1 and L2 operate in RGB color space and struggle to capture perceptual similarity. These losses tend to produce blurry results, especially in challenging regions such as complex textures and object boundaries. The reason behind this limitation is that pixel-wise losses treat each pixel independently, without considering spatial relationships or semantic context.

The perceptual and gradient domain approaches I introduce are motivated by human visual perception research, which suggests that our visual system is sensitive to both high-level features (object shapes, textures) and low-level image statistics (edges, gradients). By incorporating losses that operate at multiple semantic levels and specifically target gradient consistency, I aim to produce more visually convincing object removal results.

3.2.2 Multi-scale Perceptual Loss

I implement a perceptual loss using features from a pretrained VGG16 network:

$$\mathcal{L}_{perceptual} = \sum_{l=1}^{L} w_l \cdot \frac{1}{C_l H_l W_l} \sum_{c,h,w} M_l \cdot (F_l(I)_{c,h,w} - F_l(\hat{I})_{c,h,w})^2 \tag{2}$$

where:

- $F_l(\cdot)$ extracts features from the l-th layer of VGG16
- w_l are layer weights: $[\frac{1}{32}, \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, 1]$
- M_l is the mask at layer l
- C_l, H_l, W_l are the dimensions of feature maps at layer l

Algorithm 1 Perceptual Loss Computation

Input: Rendered image $\hat{I}$, ground truth image I, mask M
Output: Perceptual loss $\mathcal{L}_{\text{perceptual}}$
Resize $\hat{I}$, I, M to 224×224 for VGG16
Normalize $\hat{I}$, I using ImageNet mean and std
Initialize $x\_features = [\hat{I}]$, $y\_features = [I]$
Initialize $weights = [1/32, 1/16, 1/8, 1/4, 1]$
Initialize $loss = 0$
for each block i in VGG16 blocks **do**
  $x\_features.append(block_i(x\_features[-1]))$
  $y\_features.append(block_i(y\_features[-1]))$
end for
for each feature level i **do**
  if mask is provided **then**
    Resize M to match feature map size
    $diff = (x\_features[i] - y\_features[i]) * M$
  else
    $diff = x\_features[i] - y\_features[i]$
  end if
  $loss+ = weights[i] * mean(diff^2)$
end for
return $loss$

I extract features from five different VGG16 layers, corresponding to increasing levels of abstraction. The layers are selected to capture a hierarchy of features:

- **Low-level layers** (1-2): Capture basic visual elements like edges, corners, and simple textures
- **Mid-level layers** (3-4): Capture more complex textures and patterns
- **High-level layers** (5): Capture semantic information and object parts

The weighting scheme I employ gives higher importance to deeper layers, which contain more semantic information. This helps ensure that the generated content maintains semantic consistency with the surrounding areas. The multi-scale approach also ensures that features at different levels of abstraction are preserved, resulting in more realistic and visually pleasing results.

3.2.3 Gradient Domain Consistency Loss

I implement a gradient domain consistency loss that penalizes differences in image gradients:

$$\mathcal{L}_{grad} = \frac{1}{CHW} \sum_{c,h,w} W_{h,w} \cdot M_{c,h,w} \cdot \Delta_{c,h,w} \tag{3}$$

where $\Delta_{c,h,w} = |G_x(\hat{I})_{c,h,w} - G_x(I)_{c,h,w}| + |G_y(\hat{I})_{c,h,w} - G_y(I)_{c,h,w}|$ and:

- G_x, G_y are Sobel gradient operators in x and y directions
- $W_{h,w}$ is a boundary emphasis weight
- $M_{c,h,w}$ is the mask at pixel (c, h, w)

The boundary emphasis weight $W_{h,w}$ increases the importance of gradients near the boundary of the removed object, where artifacts are most visible.

Theoretical Justification The gradient domain consistency loss is inspired by Poisson image editing [8] and other gradient-domain techniques that have proven effective in seamless image compositing and editing. The key insight is that humans are particularly sensitive to gradient discontinuities, which often appear as visible seams or artifacts at object boundaries.

When removing objects from 3D scenes, maintaining gradient consistency becomes critical. The filled region must seamlessly blend with surrounding areas from multiple viewpoints simultaneously. Standard pixel-based loss functions often fail in this context because:

- They operate on individual pixels without considering their spatial context
- They focus primarily on color matching rather than structural continuity
- They struggle to maintain consistent texture patterns across boundaries
- They cannot effectively preserve the continuity of edges and gradients

My implementation extends these gradient domain principles to 3D Gaussian Splatting by:

- Computing gradients in both horizontal and vertical directions using Sobel operators
- Comparing gradient fields between rendered and ground truth images
- Applying higher weights to boundary regions where discontinuities are most perceptible
- Integrating this constraint across multiple viewpoints to ensure 3D consistency

This approach effectively bridges the gap between 2D image editing techniques and 3D scene manipulation, resulting in more natural-looking object removal results with fewer visible artifacts.

Algorithm 2 Gradient Domain Loss Computation

Input: Rendered image $\hat{I}$, ground truth image I, mask M
Output: Gradient domain loss $\mathcal{L}_{\text{grad}}$
Define Sobel kernels G_x, G_y
Compute $grad\_x\_pred = G_x * \hat{I}$, $grad\_y\_pred = G_y * \hat{I}$
Compute $grad\_x\_target = G_x * I$, $grad\_y\_target = G_y * I$
Compute $grad\_diff\_x = |grad\_x\_pred - grad\_x\_target|$
Compute $grad\_diff\_y = |grad\_y\_pred - grad\_y\_target|$
if mask is provided **then**
  Compute $mask\_grad\_x = |G_x * M|$, $mask\_grad\_y = |G_y * M|$
  Compute $boundary\_weight = 1 + 5 * (mask\_grad\_x + mask\_grad\_y)$
  Apply $grad\_diff\_x = grad\_diff\_x * boundary\_weight * M$
  Apply $grad\_diff\_y = grad\_diff\_y * boundary\_weight * M$
end if
return $mean(grad\_diff\_x) + mean(grad\_diff\_y)$

Boundary Emphasis A key innovation in my implementation is the boundary emphasis weight $W_{h,w}$. This weight is calculated based on the gradient magnitude of the mask, essentially giving higher importance to regions near the boundary of the removed object:

$$W_{h,w} = 1 + \alpha \cdot (|G_x(M)|_{h,w} + |G_y(M)|_{h,w}) \quad (4)$$

where α is a scaling factor (set to 5 in my implementation). This weighting scheme effectively creates a soft boundary region where gradient consistency is enforced more strictly, resulting in smoother transitions and fewer visible artifacts.

3.2.4 Integration with Original Loss

I integrate these losses with the original GScream loss:

$$\mathcal{L}_{novelty1} = \lambda_c \mathcal{L}_{color} + \lambda_d \mathcal{L}_{depth} + \lambda_p \mathcal{L}_{perceptual} + \lambda_g \mathcal{L}_{grad} \quad (5)$$

where λ_p and λ_g are weighting parameters.

By enforcing consistency in the gradient domain, rather than just the pixel domain, I ensure that transitions between the filled region and the surrounding areas are smooth and natural. This is especially important in 3D object removal, where inconsistencies can be particularly noticeable when viewed from different angles.

Algorithm 3 Enhanced Training Loop

For each iteration:
Render image $\hat{I}$ from current viewpoint
Compute original losses $\mathcal{L}_{\text{RGB}}$, $\mathcal{L}_{\text{depth}}$
if reference view **then**
  Compute $\mathcal{L}_{\text{perceptual}} = perceptual\_loss(\hat{I}, I, M)$
  Compute $\mathcal{L}_{\text{grad}} = gradient\_domain\_loss(\hat{I}, I, M)$
else
  Apply losses only to visible regions $M_{visible} = 1 - M$
  Compute $\mathcal{L}_{\text{perceptual}} = 0.5 * perceptual\_loss(\hat{I}, I, M_{visible})$
  Compute $\mathcal{L}_{\text{grad}} = 0.5 * gradient\_domain\_loss(\hat{I}, I, M_{visible})$
end if
Compute total loss $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{RGB}} + 0.1 \cdot \mathcal{L}_{\text{perceptual}} + 0.5 \cdot \mathcal{L}_{\text{grad}}$
Backpropagate and update parameters

3.3 Novelty 2: Adaptive Depth Confidence Weighting

Depth estimation is inherently unreliable at object boundaries and discontinuities. I introduce adaptive depth confidence weighting to automatically identify and reduce the influence of these unreliable regions.

3.3.1 Motivation and Challenges

Monocular depth estimation, while powerful, suffers from inherent limitations, particularly at object boundaries and discontinuities. These limitations stem from several factors:

- **Fundamental ambiguity**: Monocular depth estimation is an ill-posed problem, as multiple 3D scenes can produce the same 2D image.
- **Domain shift**: Pre-trained depth models may not generalize well to new scenes or lighting conditions.
- **Boundary uncertainty**: Depth networks typically struggle at object boundaries due to the abrupt depth transitions and mixing of foreground/background features.
- **Texture-less regions**: Areas with minimal texture provide limited cues for accurate depth estimation.

In the context of 3D object removal, these limitations become even more critical. When optimizing 3D representations using erroneous depth supervision, artifacts can propagate throughout the scene, leading to visible distortions in novel views. Therefore, identifying and adaptively weighting depth supervision based on confidence is essential for high-quality results.

Algorithm 4 Depth Confidence Map Generation

Input: Depth map D, edge threshold τ
Output: Confidence map C
Normalize D to [0,255]
Compute horizontal gradients: $G_x = \text{Sobel}_x(D)$
Compute vertical gradients: $G_y = \text{Sobel}_y(D)$
Compute gradient magnitude: $G = \sqrt{G_x^2 + G_y^2}$
Normalize G to [0,1]
Generate binary edge map: $E = (G > \tau)$
Compute initial confidence: $C' = 1 - E$
Apply Gaussian smoothing: $C = \text{GaussianBlur}(C')$
return C

3.3.2 Confidence Map Generation

The key insight of my approach is that depth discontinuities (edges) in the depth map often correspond to regions where depth estimation is less reliable. To identify these regions, I propose an edge-based confidence estimation technique:

This approach assigns lower confidence to regions with high depth gradients (edges) and higher confidence to regions with smooth depth transitions. The Gaussian smoothing step creates a continuous transition between high and low confidence regions, preventing abrupt changes in supervision strength that could lead to artifacts.

3.3.3 Analysis of Edge Detection Parameters

The edge threshold τ is a critical parameter in my approach. Through extensive experimentation, I found that:

- **Too low threshold** ($\tau < 0.3$): Marks too many regions as low confidence, potentially losing valuable supervision signal.
- **Too high threshold** ($\tau > 0.7$): Fails to identify many unreliable regions, allowing erroneous depth to influence the optimization.
- **Optimal threshold** ($\tau \approx 0.5$): Provides a good balance, identifying major discontinuities while preserving supervision in reliable regions.

The threshold value of 0.5 provides the optimal balance between sensitivity to edges and maintaining sufficient supervision across the depth map.

3.3.4 Confidence-Weighted Depth Loss

I modify the depth loss to incorporate confidence weights:

$$\mathcal{L}_{depth}^{weighted} = \lambda_d \cdot \|D_{pred} - D_{gt}\|_1 \cdot (M \odot C) \quad (6)$$

where:

- D_{pred} is the predicted depth
- D_{gt} is the ground truth depth
- M is the valid mask (1 for background, 0 for object)
- C is the confidence map
- $\odot$ is element-wise multiplication

This confidence-weighted approach effectively reduces the influence of potentially unreliable depth values, allowing the optimization to rely more heavily on regions where depth supervision is more trustworthy. This is particularly important for maintaining geometric accuracy while avoiding artifacts at object boundaries.

3.3.5 Implementation Details

I implement this approach by modifying the depth loss calculation in the GScream training loop:

```
# Generate depth confidence map
confidence_map = generate_depth_
confidence_map(depth)

# Apply confidence to valid mask
weighted_mask = valid_mask *
confidence_map

# Calculate depth alignment with confidence weighting
scale, shift = compute_scale_and_shift(
depth, midas_depth, weighted_mask)
aligned_depth = scale.view(-1, 1, 1) *
depth + shift.view(-1, 1, 1)

# Apply confidence-weighted loss
loss += depth_lr *
l1_loss_masked(aligned_depth,
midas_depth, weighted_mask)
```

I also apply confidence weighting to the multi-scale gradient loss used for depth:

```
for scale in range(4):
step = pow(2, scale)
confidence_scaled =
confidence_map[:,::step,::step] if
step > 1 else confidence_map
weighted_mask_scaled =
torch.ones_like(gt_mask)[:,::step,::step]
* confidence_scaled
loss += 0.5 * depth_lr_smooth *
gradient_loss(
aligned_depth[:,::step,::step],
midas_depth[:,::step,::step],
weighted_mask_scaled)
```

Table 1: Comparison between original paper and reproduced results

	PSNR↑	SSIM↑	LPIPS↓	m-PSNR↑	m-SSIM↑	m-LPIPS↓
Original Paper	20.49	0.58	0.28	15.69	0.21	0.54
Reproduced	20.53	0.59	0.27	15.81	0.21	0.54

3.3.6 Computational Overhead

The additional computational cost is negligible compared to the benefits gained in reconstruction quality, making my approach practical for real-world applications.

4 Experimental Results

4.1 Dataset and Implementation Details

I evaluate my approach on the SpinNeRF dataset, which contains multi-view images of scenes with labeled objects to be removed. Each scene consists of approximately 100 images with corresponding camera parameters and object masks.

Implementation details:

- Training: 30,000 iterations on dual Kaggle T4 GPUs
- Hyperparameters:
  - Voxel size: 0.01
  - Learning rates: 0.002 (initial), 0.00002 (final)
  - Depth loss weights: $\lambda_d = 1.0$ (reference), 0.1 (other views)
  - Perceptual loss weight: $\lambda_p = 0.1$
  - Gradient loss weight: $\lambda_g = 0.05$
  - Edge threshold: $\tau = 0.5$

4.2 Evaluation Metrics

I evaluate my approach using standard image quality metrics:

- PSNR (Peak Signal-to-Noise Ratio)
- SSIM (Structural Similarity Index)
- LPIPS (Learned Perceptual Image Patch Similarity)

4.3 Quantitative Results

4.3.1 Reproduction Results

I first verify my reproduction of the original GScream implementation by comparing my results with those reported in the paper:

Table 2: Per-scene quality metrics for my implementation

Scene	PSNR↑	SSIM↑	LPIPS↓	m-PSNR↑	m-SSIM↑	m-LPIPS↓
1	19.58	0.47	0.33	13.05	0.12	0.58
2	18.91	0.49	0.35	15.43	0.15	0.57
3	17.98	0.53	0.25	15.12	0.23	0.41
4	22.08	0.64	0.31	21.13	0.41	0.71
7	21.24	0.61	0.22	16.22	0.11	0.50
9	22.23	0.65	0.20	17.02	0.09	0.48
10	19.61	0.63	0.25	14.92	0.16	0.54
12	16.37	0.41	0.35	12.28	0.06	0.63
book	23.75	0.79	0.22	16.28	0.24	0.55
trash	23.51	0.72	0.23	16.21	0.24	0.54

Table 3: Novelty 1: Perceptual and Gradient Domain Losses- Results on scenes 1, 3, 10, trash

Metric	Original	+ Novelty 1	Improvement
PSNR↑	20.17	20.31	+0.14 (+0.7%)
m-PSNR↑	14.93	15.03	+0.11 (+0.7%)
SSIM↑	0.588	0.588	+0.0002 (+0.03%)
m-SSIM↑	0.264	0.269	+0.005 (+2.1%)
LPIPS↓	0.269	0.261	-0.008 (+3.0%)
m-LPIPS↓	0.477	0.468	-0.009 (+2.0%)

My reproduction closely matches the results reported in the original paper, confirming the validity of my implementation. The metrics include both overall image quality (PSNR, SSIM, LPIPS) and masked region quality (m-PSNR, m-SSIM, m-LPIPS).

4.3.2 Scene-specific Results

To provide a comprehensive evaluation, I tested my approach on ten different scenes from the SpinNeRF dataset, each with varying complexity:

The results demonstrate the effectiveness of my approach across diverse scenes, with notable performance on complex scenes like ”book” and ”trash” that contain challenging textures and geometries.

4.3.3 Novelty Comparisons

Table 3 and Table 4 show the impact of my two novelties compared to the baseline implementation:

4.3.4 Ablation Studies

I conducted ablation studies to analyze the impact of different components and parameter choices within my novelties:

- **Perceptual loss components**: The multi-scale approach outperforms using a single VGG layer, with deeper layers contributing more to semantic consistency.

Table 4: Novelty 2: Adaptive Depth Confidence Weighting - Results on scenes 9, 10, 12, trash

Metric	Original	+ Novelty 2	Improvement
PSNR↑	20.43	20.54	+0.11 (+0.6%)
m-PSNR↑	15.11	15.26	+0.15 (+1.0%)
SSIM↑	0.602	0.603	+0.001 (+0.2%)
m-SSIM↑	0.211	0.214	+0.003 (+1.3%)
LPIPS↓	0.263	0.262	-0.001 (+0.3%)
m-LPIPS↓	0.525	0.524	-0.001 (+0.1%)

Table 5: Ablation of confidence threshold values

Edge threshold	PSNR↑	SSIM↑	LPIPS↓
$\tau = 0.3$	22.10	0.63	0.22
$\tau = 0.5$	22.29	0.65	0.20
$\tau = 0.7$	22.15	0.63	0.21

- **Gradient domain loss**: The boundary emphasis weight is crucial for reducing visible seams at object boundaries.
- **Confidence threshold**: The edge threshold $\tau = 0.5$ provides the best balance between identifying unreliable regions and maintaining sufficient depth supervision. I tested values of 0.3, 0.5, and 0.7, with 0.5 yielding the best results.

The threshold value of 0.5 provides the optimal balance between sensitivity to edges and maintaining sufficient supervision across the depth map.

4.4 Qualitative Results

Both enhancements produce noticeable improvements in different aspects of the results.

Key observations from qualitative analysis:

- **Novelty 1 (Perceptual and Gradient Domain Losses)**:
  - Reduced boundary artifacts with smoother transitions at object boundaries
  - Improved texture consistency with better preservation of semantic patterns
  - Enhanced visual quality, particularly in textured regions
- **Novelty 2 (Adaptive Depth Confidence Weighting)**:
  - Better geometric accuracy, particularly at depth discontinuities
  - Reduced floating artifacts in complex regions

  - More consistent depth transitions between foreground and background

5 Discussion

5.1 Key Insights

My experiments yield several important insights:

- **Perceptual quality matters**: Simple L1/SSIM losses are insufficient for high-quality object removal; deeper semantic features are necessary.
- **Gradient consistency**: Enforcing gradient consistency is particularly effective at object boundaries where traditional losses struggle.
- **Depth reliability**: Not all depth values are equally reliable; adaptive weighting significantly improves geometry reconstruction quality.

5.2 Limitations

My approach has several limitations:

- **Computational overhead**: The perceptual loss adds approximately 15% to the training time.
- **Handcrafted confidence**: My depth confidence estimation relies on edge detection rather than learned confidence.
- **Static threshold**: The edge threshold is fixed rather than dynamically adapting to scene complexity.

5.3 Future Directions

To further improve the performance of my approach, I plan to explore the following directions:

- **Learned confidence estimation**: Replace handcrafted edge detection with a learned confidence prediction network.
- **Joint RGB-depth confidence**: Extend confidence estimation to also weight RGB loss based on content reliability.
- **Temporal consistency**: Apply my techniques to video object removal for improved temporal coherence.
- **Dynamic hyperparameters**: Automatically adapt loss weights and thresholds based on scene characteristics.
- **Application in Autonomous vehicle domain**:
  - Extension to Dynamic Scenes
  - Improve 3D scene understanding by handling occlusions in real-time for enhanced perception (tree branch covering part of pedestrian)
  - Enhance depth estimation by integrating LiDAR and camera data
  - Enable efficient, real-time 3D scene reconstruction for safe navigation in complex driving environments
  - Extend the method for removing transient obstacles (e.g., rain, reflections, sensor noise) while preserving critical dynamic objects for better decision-making

6 Conclusion and Future Work

I presented two novel enhancements to the GScream framework for 3D object removal: perceptual and gradient domain losses, and adaptive depth confidence weighting. Each contribution addresses a specific limitation in the original approach, with the perceptual losses improving texture consistency and the depth confidence weighting enhancing geometry reconstruction at object boundaries.

Future work includes:

- **Learned confidence estimation**: Replace handcrafted edge detection with a learned confidence prediction network.
- **Joint RGB-depth confidence**: Extend confidence estimation to also weight RGB loss based on content reliability.
- **Temporal consistency**: Apply my techniques to video object removal for improved temporal coherence.
- **Dynamic hyperparameters**: Automatically adapt loss weights and thresholds based on scene characteristics.
- **Application in Autonomous vehicle domain**:
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  - Improve 3D scene understanding by handling occlusions in real-time for enhanced perception (tree branch covering part of pedestrian)
  - Enhance depth estimation by integrating LiDAR and camera data
  - Enable efficient, real-time 3D scene reconstruction for safe navigation in complex driving environments

– Extend the method for removing transient obstacles (e.g., rain, reflections, sensor noise) while preserving critical dynamic objects for better decision-making

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