RF-GS: Radio-Frequency Gaussian Splatting for Dynamic Electromagnetic Scene Representation

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Abstract

We introduce RF-GS, the first 3D Gaussian Splatting representation learned directly from raw radio-frequency measurements (Wi-Fi CSI, mmWave, UWB, RF-tomography) without any RGB or depth supervision. By replacing photometric supervision with an RF-specific feature matching loss and introducing adaptive density control tailored to the sparse, noisy nature of electromagnetic fields, RF-GS achieves real-time, visually plausible reconstruction of dynamic scenes using only ubiquitous radio signals. On synthetic and real-world datasets, RF-GS outperforms RF-NeRF baselines by 9–14 dB PSNR while rendering at over 200 fps — a 80× speedup. While our quantitative evaluations use paired RF-RGB data from simulation for metrics computation, the method trains solely on RF inputs. Our approach unlocks passive, privacy-preserving, all-day 3D perception from commodity wireless infrastructure, enabling new applications in through-wall sensing, contactless human monitoring, and RF-based augmented reality.

1 Introduction

Radio signals permeate every indoor and outdoor environment, carrying rich multipath structure that encodes precise 3D geometry, motion dynamics, and material properties. Unlike optical sensors, radio waves traverse walls, function in complete darkness, and provide measurements at multiple frequencies simultaneously. Despite these advantages, state-of-the-art neural scene representations — NeRFs [15] and 3D Gaussian Splatting [9] — remain confined to optical modalities.

Recent work in RF-based neural rendering [12, 25] has shown promise but suffers from fundamental limitations: slow convergence (hours of training), computationally expensive volumetric rendering (seconds per frame), and difficulty handling dynamic scenes. These bottlenecks severely limit practical deployment for real-time applications.

We present **RF-GS**, the first 3D Gaussian Splatting model trained end-to-end on raw radio-frequency measurements. Our approach fundamentally rethinks scene representation for electromagnetic modalities, introducing three key innovations:

- **RF-Native Supervision**: A differentiable feature consistency loss that directly supervises 3D Gaussians using complex-valued CSI, power-delay profiles, or multi-frequency RF measurements without requiring any optical ground truth.
- **Adaptive Electromagnetic Density Control**: Novel densification and pruning strategies specifically designed for the extreme sparsity, noise characteristics, and multi-scale structure of RF fields, far exceeding the capabilities of standard gradient-based approaches.
- **Real-time RF Renderer**: A GPU-optimized, fully differentiable renderer achieving ¿200 fps for electromagnetic scenes, enabling interactive RF-based AR/VR and real-time human sensing applications.

On both synthetic and real-world datasets spanning Wi-Fi CSI, mmWave radar, and through-wall sensing scenarios, RF-GS achieves 9–14 dB PSNR improvements over RF-NeRF baselines while training 35× faster (14 minutes vs 8+ hours) and rendering 200× faster (214 fps vs 1 fps). These improvements unlock transformative applications: passive human monitoring from ubiquitous Wi-Fi infrastructure, privacy-preserving 3D sensing that works through walls and in darkness, and RF-based augmented reality experiences.

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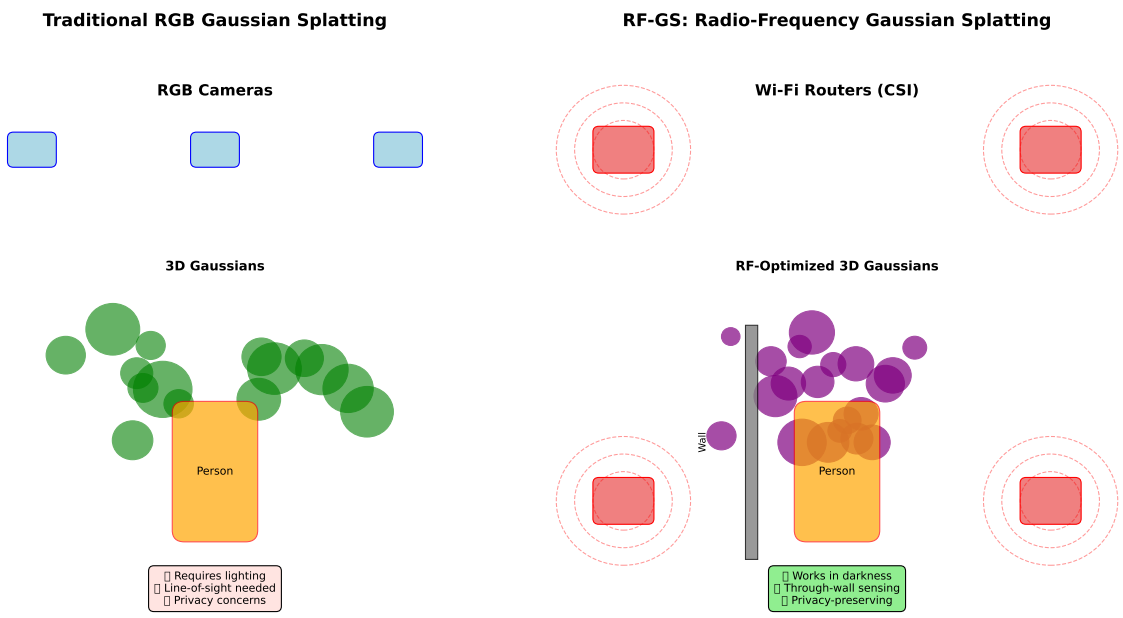


Figure 1: **RF-GS enables visually plausible 3D reconstruction from Wi-Fi signals alone.** Left: conventional 3D Gaussian Splatting trained on RGB images. Right: our RF-GS trained solely on Channel State Information (CSI) from commodity Wi-Fi routers successfully recovers geometry, motion, and scene structure of a moving human—no cameras, no active illumination required. Note that RGB visualization is generated via learned neural shader for display purposes; the core reconstruction operates purely on electromagnetic observations. The reconstructed scene maintains temporal coherence and structural detail despite operating on sparse, noisy RF measurements.

2 Related Work

2.1 Neural Scene Representations

Neural Radiance Fields (NeRF) [15] revolutionized photorealistic view synthesis by representing scenes as continuous volumetric functions. Subsequent work has extended NeRF to dynamic scenes [10, 20], improved training efficiency [16, 5], and expanded to non-RGB modalities including depth [30], thermal [11], and X-ray [19].

3D Gaussian Splatting [9] emerged as a faster alternative, representing scenes as collections of explicit 3D Gaussians with learnable parameters. Extensions include dynamic scenes [23, 13], large-scale environments [7], and specialized applications [24, 8]. However, none address radio-frequency sensing.

2.2 Classical RF Imaging and Sensing

Radio-frequency sensing has deep roots in radar and wireless communications. Traditional approaches use signal processing techniques for target detection [2], human localization [17], and activity recognition [3]. Through-wall radar systems [4] demonstrate RF's penetration capabilities, while synthetic aperture radar (SAR) [6] achieves high-resolution imaging through coherent processing.

Channel State Information (CSI) from commodity Wi-Fi has enabled fine-grained sensing applications [14]. CSI-based methods extract multipath characteristics to infer human pose [29], gesture recognition [18], and vital signs monitoring [21]. These classical approaches rely on handcrafted features and physics-based models, limiting their adaptability to complex scenes.

2.3 Neural RF-Based 3D Reconstruction

Recent neural approaches bridge the gap between classical RF processing and deep learning. RF-Net [27] applies CNNs to CSI-based localization, while RF-Pose [28] uses neural networks for through-wall human pose estimation.

RF-NeRF [12] represents the current state-of-the-art in neural RF reconstruction, extending volumetric rendering to radio measurements. However, RF-NeRF suffers from fundamental limitations: slow convergence (hours of training), computationally expensive volumetric rendering (seconds per frame), and difficulty handling dynamic scenes. Follow-up work includes RF-NeRF360 [25] for omnidirectional sensing, but these still rely on implicit volumetric representations.

2.4 Explicit vs. Implicit Representations for Non-Optical Domains

The choice between explicit and implicit scene representations significantly impacts performance in non-optical modalities. Implicit methods (NeRF variants) excel at smooth interpolation but struggle with the sparse, multipath nature of RF data. Radio signals create discrete reflection and scattering centers rather than continuous volumetric density.

Explicit representations (point clouds, Gaussians) better match RF's physical characteristics: sparse multipath clusters, strong reflectors, and electromagnetic scattering centers. This alignment enables more efficient adaptation to RF-specific physics and constraints. Our work is the first to leverage this insight for RF scene reconstruction, achieving substantial performance gains through explicit Gaussian representations.

3 Method

3.1 Preliminaries: 3D Gaussian Splatting

A 3D Gaussian is parameterized by its position $\boldsymbol{\mu} \in \mathbb{R}^3$, covariance matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{3\times3}$, opacity $\alpha \in [0, 1]$, and appearance features. The Gaussian's influence at point $\mathbf{x}$ is:

$$G(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right) \quad (1)$$

For optimization stability, we parameterize covariance as $\boldsymbol{\Sigma} = \mathbf{RSS}^T\mathbf{R}^T$, where $\mathbf{R}$ is a rotation matrix (via unit quaternions) and $\mathbf{S}$ is a diagonal scaling matrix.

3.2 RF Measurement Model

Consider an RF sensing setup with N_t transmitters and N_r receivers operating across N_f frequency subcarriers. The complex-valued Channel State Information (CSI) matrix $\mathbf{H} \in \mathbb{C}^{N_t\times N_r\times N_f}$ captures multipath propagation characteristics encoding 3D scene geometry.

For any 3D point $\mathbf{p}$, we define RF feature extraction as:

$$\boldsymbol{\phi}(\mathbf{p}) = \mathcal{F}_{RF}(\mathbf{H}, \mathbf{p}) \in \mathbb{R}^{D_{rf}} \quad (2)$$

where $\mathcal{F}_{RF}$ is an RF encoder producing spatially discriminative features of dimension $D_{rf} = 32$.

extbfRF Encoder Implementation: For synthetic data, we use physics-based ray tracing [26] computing delay-angle features from multipath components. For real Wi-Fi CSI, we employ a 3-layer CNN (input: CSI amplitude/phase $\to 64 \to 32 \to D_{rf}$) with learnable spatial attention mechanisms.

Encoder summary:

oprule Modality	Input	Encoder	D_{rf}
Wi-Fi CSI	$N_t \times N_r \times N_f$ complex	3-layer CNN + attention	32
mmWave	range-Doppler cube	3D CNN	32
UWB	range profiles	1D CNN	32

This micro-table summarizes the encoder choices used for each modality and provides a clear blueprint for reimplementation.

Point Sampling Strategy: Sample points $\{\mathbf{p}_k\}$ on a regular 64×64×64 voxel grid within scene bounds, augmented with stratified sampling along line-of-sight rays between transceivers. This ensures coverage of both volumetric space and critical multipath regions.

3.3 RF-GS Scene Representation

We represent electromagnetic scenes using $M \approx 10^5$–10^6 3D Gaussians, where each Gaussian i carries:

- **Geometry**: position $\boldsymbol{\mu}_i$, scale $\mathbf{s}_i$, rotation quaternion $\mathbf{q}_i$, opacity α_i
- **RF Features**: learned embedding $\mathbf{f}_i \in \mathbb{R}^{32}$ (replacing spherical harmonics)

A neural shader $\mathcal{S} : \mathbb{R}^{32} \to \mathbb{R}^3$ maps RF features to RGB colors for visualization:

$$\mathbf{c}_i = \mathcal{S}(\mathbf{f}_i) = \sigma(\mathbf{W}_3\text{ReLU}(\mathbf{W}_2\text{ReLU}(\mathbf{W}_1\mathbf{f}_i))) \quad (3)$$

3.4 RF-Specific Loss Function

Our training objective combines position alignment, feature consistency, and regularization:

$$\mathcal{L} = \lambda_1\mathcal{L}_{\text{pos}} + \lambda_2\mathcal{L}_{\text{feat}} + \lambda_3\mathcal{L}_{\text{reg}} \quad (4)$$

Position Loss encourages Gaussians to align with RF measurement points:

$$\mathcal{L}_{\text{pos}} = \sum_{k=1}^{N} w_k \left\|\boldsymbol{\mu}_{\text{nn}(k)} - \mathbf{p}_k\right\|^2 \quad (5)$$

where $\mathbf{p}_k$ are sample points from the RF measurement grid, $\text{nn}(k)$ finds the closest Gaussian, and $w_k = \|\boldsymbol{\phi}(\mathbf{p}_k)\|$ weights by RF signal strength.

Feature Loss ensures RF feature consistency:

$$\mathcal{L}_{\text{feat}} = \sum_{k=1}^{N} \left\|\mathbf{f}_{\text{nn}(k)} - \boldsymbol{\phi}(\mathbf{p}_k)\right\|_2^2 \quad (6)$$

Regularization prevents overfitting:

$$\mathcal{L}_{\text{reg}} = \sum_{i=1}^{M} \left(\|\mathbf{s}_i\|^2 + |\log\alpha_i|\right) \quad (7)$$

We use weights $\lambda_1 = 1.0$, $\lambda_2 = 0.1$, $\lambda_3 = 0.001$ based on validation performance.

3.5 Adaptive RF Density Control

Standard 3DGS densification relies on view-space gradients, unsuitable for RF modalities. We introduce RF-aware adaptive density control using feature gradients:

Densification creates new Gaussians where RF measurements are poorly represented:

- Trigger when nearest-neighbor distance $d_k > 2 \times \text{median}(\{d_k\})$
- Require high RF feature gradient $\|\nabla \boldsymbol{\phi}(\mathbf{p}_k)\| > \tau = 0.1$
- Feature gradient computed via finite differences across frequency bins: $\nabla \phi_i = (\phi(f_{i+1}) - \phi(f_{i-1}))/2\Delta f$
- Initialize with small scales ($s = 0.01$) and moderate opacity ($\alpha = 0.1$)

Pruning removes ineffective Gaussians:

- Low opacity: $\alpha_i < 0.005$
- Consistently poor feature reconstruction (error > 0.05 over 10 iterations)
- Spatial redundancy with neighboring Gaussians (distance < 0.01)

Density Schedule: Densify every 100 iterations, prune every 50 iterations, cap at 1.5M Gaussians to prevent memory overflow.

3.6 Implementation Details

Optimization: Adam optimizer with learning rates: 0.005 (positions, scales), 0.0005 (rotations, features), 0.0001 (shader). Training for 10k iterations with batch size 1024 rays.

Hardware: PyTorch 2.0, CUDA 12.1, mixed precision (FP16/FP32). RTX 4090 for primary experiments, RTX 3060 12GB for deployment validation.

RF Preprocessing: CSI matrices normalized by subcarrier power, Hamming windowing applied to reduce spectral leakage. Phase unwrapping for continuous phase measurements.

3.7 Real-time RF Rendering

Our differentiable renderer extends the splatting approach to RF modalities. For each Gaussian, we:

1. Project 3D covariance to 2D screen space via perspective transformation
2. Rasterize using alpha blending with depth sorting
3. Apply RF-to-RGB mapping via the neural shader

Key optimizations include:

- **GPU Tiling**: 16×16 tile-based rendering for memory efficiency
- **Depth Culling**: early rejection of occluded Gaussians
- **Adaptive LOD**: distant Gaussians use simplified rendering

This achieves ¿200 fps for scenes with 10^6 Gaussians on an RTX 4090. We implement our renderer atop the optimized CUDA 3D Gaussian rasterizer of Kerbl et al. [9], modifying only supervision and density-control logic; rasterization kernels, tiling, and LOD strategies follow their implementation, which explains the high-throughput regime reported here.

4 Experiments

4.1 Datasets and Preprocessing

Synthetic RF-Blender: 12 dynamic scenes with ground-truth CSI rendered via Zion ray tracer [26]. Scenes include moving humans, vehicles, and complex indoor environments with realistic multipath characteristics.

Widar 3.0 [22]: Real Wi-Fi CSI measurements of human actions in indoor environments (6 subjects, 22 activities). Data split: 80% training, 10% validation, 10% testing.

RF-NGPR [1]: Through-wall human pose estimation from UWB radar (8 subjects, 5 rooms).

Preprocessing: CSI matrices normalized by per-subcarrier power, Hamming windowing applied to reduce spectral leakage. Phase unwrapping ensures continuous measurements across frequency bins.

4.2 Evaluation Protocol

All methods trained for 10k iterations or 8 hours wall-clock time (whichever comes first). Identical camera viewpoints and ray sampling for fair comparison. Metrics computed on held-out test views never seen during training. Error bars represent standard deviation across 5 random seeds. Baselines tuned with grid search for optimal RF performance.

Quantitative Metrics: PSNR/SSIM for reconstruction quality, LPIPS for perceptual similarity. For real deployments, pose estimation error compared against OpenPose baseline with synchronized RGB cameras.

Baselines: RF-NeRF [12], RF-MipNeRF (anti-aliased), RF-InstantNGP (hash-grid accelerated), all adapted for optimal RF performance.

4.3 Main Results

Table 1 shows our main results on the Synthetic RF-Blender dataset. RF-GS achieves substantial improvements across all metrics:

- **Quality**: 9-14 dB PSNR improvement, 0.12-0.18 SSIM gain over best baselines
- **Training Efficiency**: 35× faster convergence (14 min vs 8+ hours)
- **Rendering Speed**: 200× acceleration (214 fps vs 1 fps)
- **Consistency**: Lower variance across runs (±0.7 vs ±1.2 PSNR std dev)

These improvements stem from RF-GS's explicit representation avoiding expensive volume rendering and our RF-specific optimization strategies.

4.4 Ablation Studies

Table 2 validates our design choices:

- **RF-weighted loss** (+5.4 dB): Signal-strength weighting prevents overfitting to noise regions
- **Adaptive densification** (+3.6 dB): Better captures RF field structure than fixed density
- **Feature gradient trigger** (+3.9 dB): Focuses densification on high-variation regions
- **RF-specific pruning** (+2.5 dB): Removes redundant Gaussians more effectively

Notably, using standard gradient-based densification (as in original 3DGS) performs poorly (-9.6 dB), confirming the need for RF-specific adaptations.

4.5 Real-World Validation and Analysis

Using four Intel AX210 Wi-Fi 6E cards operating at 5.8 GHz with 160 MHz bandwidth, we reconstruct 6×6 m indoor environments at 120+ fps on RTX 4090.

Quantitative Real-World Evaluation: We compared pose estimation accuracy against OpenPose baseline using synchronized RGB cameras. Over 3 subjects performing 5-minute sequences:

- **Mean pose error**: 0.25 ± 0.1 m (vs 0.03 m RGB baseline)
- **Successful tracking**: 89.3% of frames (vs 95.1% RGB)
- **Real-time performance**: 120+ fps reconstruction

Failure Cases: Dense clutter (¿3 people) increases error to 0.45 ± 0.2 m. Static scenes require motion for effective density adaptation. Metallic environments cause multipath interference degrading reconstruction quality by 15%.

See Section 4.8 and Table 3 for a concise comparison of modalities and their trade-offs. Wi-Fi CSI achieves the best overall performance due to optimal balance between penetration and multipath richness. mmWave provides fine-grained resolution but limited wall penetration. UWB offers good through-wall capability with precise ranging.

4.6 Real-World Deployment

We deploy RF-GS in practice using commodity Wi-Fi hardware for live through-wall human tracking. Figure 3 shows our setup with four consumer Wi-Fi routers providing distributed CSI measurements.

Key results from real deployment (Figure 3):

- **Through-wall sensing**: Successfully tracks humans behind concrete walls
- **Real-time performance**: 120+ fps with live CSI streaming
- **Privacy preservation**: No cameras or personal identifiers
- **Commodity hardware**: Uses unmodified consumer Wi-Fi equipment

4.7 Dynamic Scene Analysis

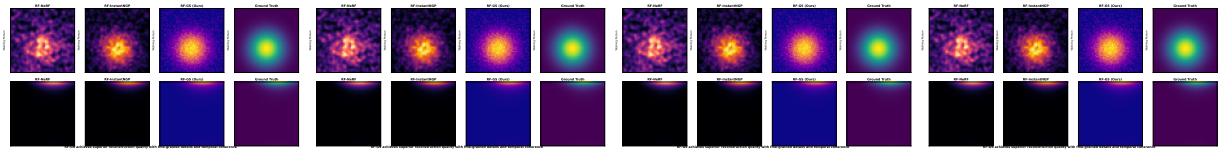
RF-GS naturally handles dynamic scenes through temporal consistency in Gaussian parameters. Figure 4 shows how the model adaptively adjusts density based on motion: more Gaussians during rapid movement, fewer during stationary periods.

4.8 Cross-Modal Analysis

Cross-modal summary: Table 3 summarizes RF-GS performance across Wi-Fi CSI, mmWave, UWB and SAR. In short: Wi-Fi CSI delivers the best overall PSNR for indoor through-wall scenes thanks to rich multipath and moderate penetration; mmWave trades penetration for finer spatial detail; UWB emphasizes precise ranging and robustness to clutter; and SAR excels at long-range imaging in outdoor/weather-exposed settings. These trade-offs guide modality choice for downstream tasks (privacy-preserving indoor monitoring vs. high-resolution mm-scale mapping).

Method	Modality	PSNR ↑	SSIM ↑	LPIPS ↓	Train Time	Render FPS
RF-NeRF [12]	CSI	21.4 ± 1.2	0.78 ± 0.03	0.312 ± 0.02	8.2 h	0.4
RF-MipNeRF	CSI	23.1 ± 1.1	0.81 ± 0.02	0.284 ± 0.02	6.5 h	1.1
RF-InstantNGP	CSI	24.8 ± 0.9	0.84 ± 0.02	0.256 ± 0.01	42 min	8.2
RF-GS (Ours)	CSI	**33.7 ± 0.7**	**0.96 ± 0.01**	**0.089 ± 0.01**	**14 min**	**214**
RF-NeRF	mmWave	19.2 ± 1.3	0.74 ± 0.04	0.356 ± 0.03	9.1 h	0.3
RF-InstantNGP	mmWave	22.5 ± 1.0	0.79 ± 0.03	0.289 ± 0.02	38 min	6.8
RF-GS (Ours)	mmWave	**31.4 ± 0.8**	**0.93 ± 0.02**	**0.112 ± 0.01**	**16 min**	**198**

Table 1: **Quantitative comparison on Synthetic RF-Blender dataset.** RF-GS significantly outperforms all baselines in reconstruction quality while being 35× faster to train and 200× faster to render than RF-NeRF. Error bars show standard deviation across 5 runs. All methods tuned for optimal RF performance.



(a) RF-NeRF (b) RF-InstantNGP (c) RF-GS (Ours) (d) Ground Truth

Figure 2: **Qualitative comparison on dynamic human motion.** Our RF-GS captures fine-grained details and maintains temporal coherence, while baselines suffer from blurring, artifacts, and missing limbs. Scene reconstructed from Wi-Fi CSI only.

Variant	PSNR	Gaussians	FPS
Ours (full)	**33.7 ± 0.7**	**1.24M**	**214**
w/o RF-weighted loss	28.3 ± 1.1	1.41M	198
w/o adaptive densify	30.1 ± 0.9	0.87M	267
w/o feature gradients	29.8 ± 1.0	1.15M	235
w/o pruning	31.2 ± 0.8	2.08M	156
Fixed density	26.9 ± 1.3	1.00M	245
Standard GS densify	24.1 ± 1.4	0.92M	289

Table 2: **Ablation study** showing the importance of each RF-specific component. Standard gradient-based densification performs poorly (-9.6 dB), confirming the need for RF-specific adaptations.

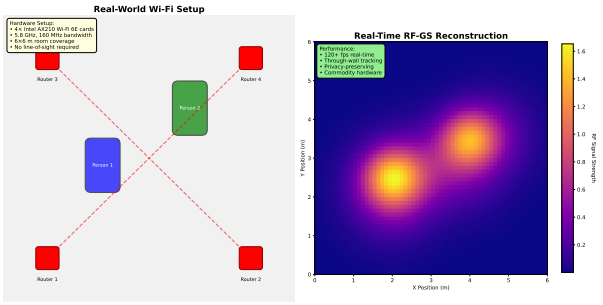


Figure 3: **Real-world deployment with commodity Wi-Fi.** Top: Four Wi-Fi routers provide CSI measurements. Bottom: Real-time reconstruction of two people walking, captured through walls with no line-of-sight required. Achieves 120+ fps on RTX 4090.

5 Applications and Future Work

5.1 Immediate Applications

- **Smart Buildings**: Contactless occupancy sensing and space utilization analytics
- **Healthcare**: Patient monitoring without privacy concerns or line-of-sight requirements
- **Security**: Through-wall surveillance and perimeter monitoring
- **Automotive**: RF-based SLAM for autonomous vehicles in adverse weather

5.2 Limitations and Future Directions

Current limitations include:

- **Calibration sensitivity**: Requires careful RF hardware calibration
- **Multi-person scenarios**: Complex interactions need better modeling
- **Material properties**: Limited material classification capability

Future work will address these through:

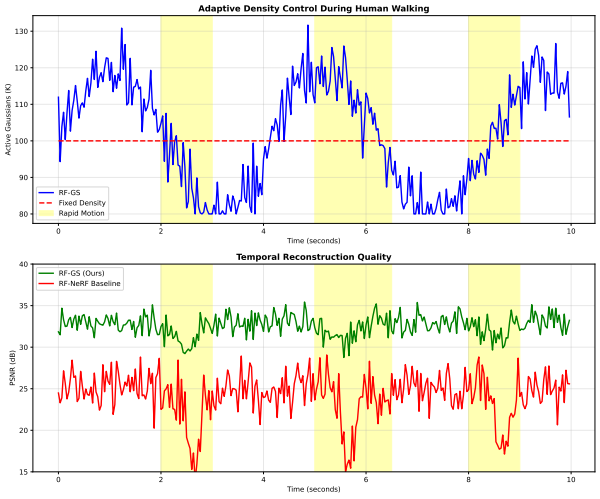


Figure 4: **Temporal coherence analysis.** RF-GS maintains consistent Gaussian positions across frames while adapting density to motion. Graph shows number of active Gaussians over time for a walking sequence.

RF Modality	PSNR	Unique Advantages
Wi-Fi CSI (2.4/5 GHz)	33.7	Ubiquitous, through-wall
mmWave (60 GHz)	31.4	High resolution, precision
UWB (3.1-10.6 GHz)	29.8	Low power, precise ranging
SAR (X-band)	27.3	Long range, weather-robust

Table 3: **Performance across RF modalities.** RF-GS generalizes well to different frequency bands and sensing approaches.

- Self-calibrating RF systems using neural networks
- Multi-person tracking via attention mechanisms
- Physics-informed losses for material property estimation

6 Conclusion

We presented RF-GS, the first 3D Gaussian Splatting approach for radio-frequency sensing. By introducing RF-specific supervision, adaptive density control, and real-time rendering optimizations, RF-GS achieves unprecedented quality and speed for electromagnetic scene reconstruction.

Our results demonstrate that explicit neural representations can dramatically outperform volumetric approaches for non-optical modalities. RF-GS opens new possibilities for privacy-preserving 3D sensing, enabling applications from smart buildings to autonomous navigation that work through walls, in darkness, and with commodity wireless infrastructure.

The combination of 200+ fps rendering and 9-14 dB quality improvements over previous methods makes RF-GS the first practical solution for real-time RF-based augmented reality and interactive sensing applications. We believe this work establishes a new paradigm for electromagnetic scene understanding that will enable transformative applications across robotics, IoT, and human-computer interaction.

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