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NeurIPS 2026

RxGS

Receiver-Generalizable 3D Gaussian Splatting for Radio-Frequency Data Synthesis

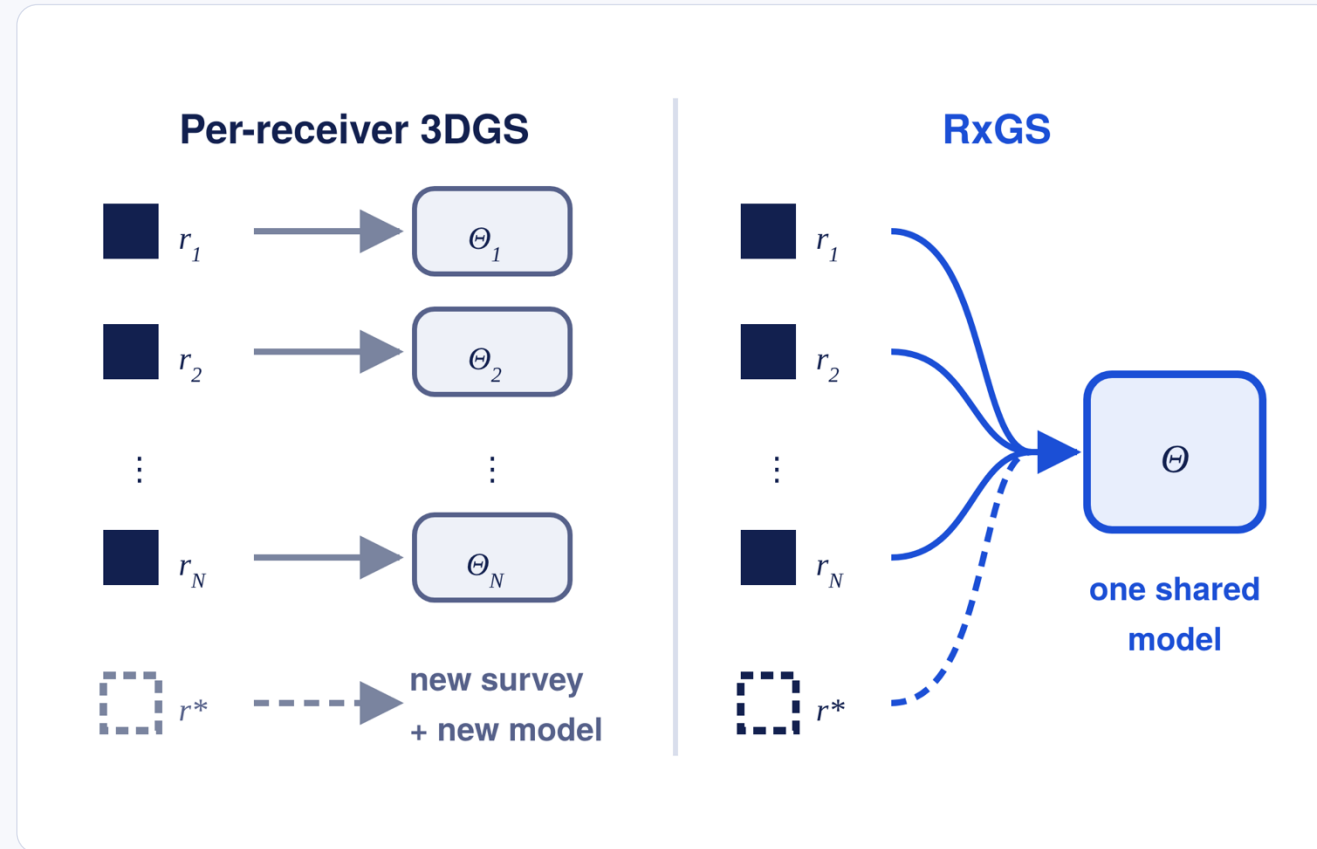
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Project page
kangyangg.com/projects/rxgs



One Model per Receiver

Existing 3DGS methods bake each fixed receiver into the model weights.



N receivers need N models

Cost grows linearly with N.

New receivers need new surveys

Plus a new checkpoint per site.

RxGS: one shared model

Receiver position is an input.

Key Insight

Walls and furniture stay put. Only the last path segment changes with the receiver.

Geometry is shared.

Radiance depends on the receiver.

Last-segment factorization (Proposition 1)

$$\phi_k \left(\hat{\mathbf{d}}_k, \mathbf{r} \right) = \eta_{\text{eff}} \left(\mathbf{p}_k, \mathbf{r} \right) \cdot \phi_k^{\text{base}} \left(\hat{\mathbf{d}}_k, \mathbf{t} \right), \quad \eta_{\text{eff}} = \underbrace{\frac{\lambda}{4\pi d_k}}_{\text{path loss}} \cdot \underbrace{e^{-j \frac{2\pi}{\lambda} d_k}}_{\text{phase}} \cdot \underbrace{T_k}_{\text{occlusion}}$$

Global + local branches

Shared plus per-scatterer

Affine modulation

Complex scale and shift

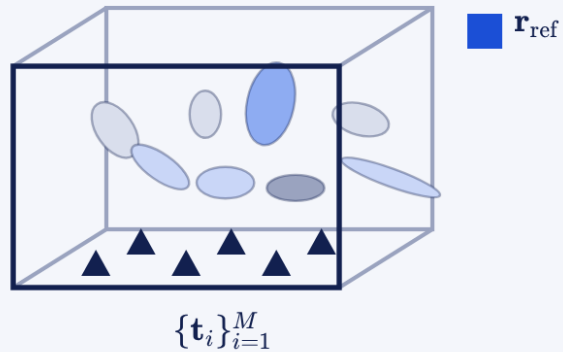
Shared weights

One MLP for all Gaussians

Two-Stage Training

Stage I learns and freezes the geometry. Stage II conditions the radiance on the receiver.

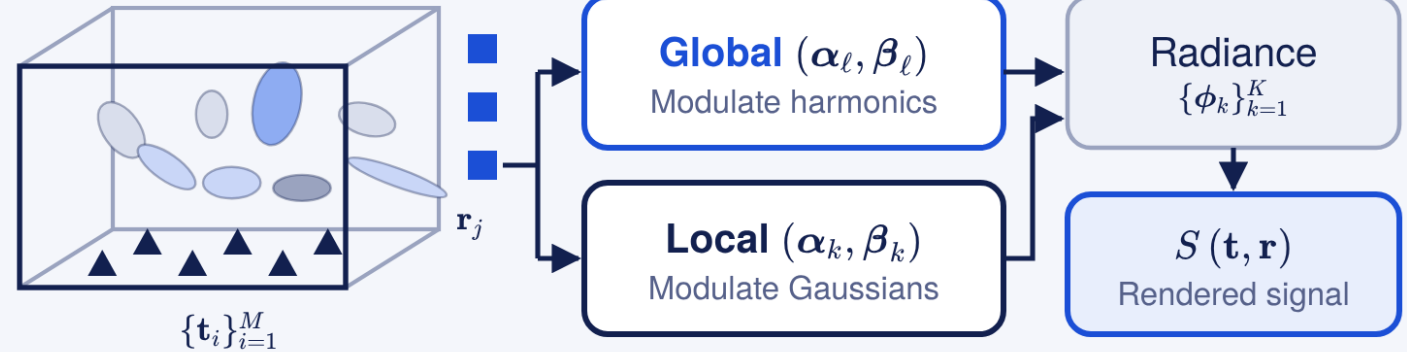
Stage I: Geometry



trainable

$\{\mathbf{p}_k, \mathbf{C}_k, \tau_k\}_{k=1}^K$

Stage II: Receiver-Conditioned Radiance



frozen

$\{\mathbf{p}_k, \mathbf{C}_k, \tau_k\}_{k=1}^K$

▲ Transmitter

■ Receiver

Receiver Conditioning

The receiver position modulates the radiance: global branch first, then local branch.

Global branch

$$(\boldsymbol{\alpha}_\ell, \boldsymbol{\beta}_\ell) = \text{MLP}_{\text{global}}([\gamma(\mathbf{r}); \mathbf{c}_\ell; \mathbf{e}_\ell])$$

$$\tilde{\boldsymbol{\phi}}_k^{(\ell)}(\mathbf{r}) = (1 + \boldsymbol{\alpha}_\ell) \odot \boldsymbol{\phi}_k^{\text{base},(\ell)} + \boldsymbol{\beta}_\ell$$

Same modulation for every Gaussian

Local branch

$$(\boldsymbol{\alpha}_k^{\text{loc}}, \boldsymbol{\beta}_k^{\text{loc}}) = \text{MLP}_{\text{local}}([\hat{\mathbf{v}}_k; d_k; T_k; \bar{\rho}_k])$$

$$\boldsymbol{\phi}_k(\hat{\mathbf{d}}_k, \mathbf{r}) = (1 + \boldsymbol{\alpha}_k^{\text{loc}}) \odot \tilde{\boldsymbol{\phi}}_k(\mathbf{r}) + \boldsymbol{\beta}_k^{\text{loc}}$$

Per-Gaussian direction, distance, and occlusion

Synthesis Accuracy

One shared model per backbone on BLE RSSI, RFID spectrum, and WiFi CSI.

Method	Models	BLE MAE ↓	RFID PSNR ↑	WiFi SNR ↑
NeRF ²	1	3.40	24.58	21.00
GRaF	1	n/a	26.40	n/a
RF-3DGS	N	4.09	23.11	21.89
RF-3DGS + RxGS	1	3.94	22.22	20.19
GSRF	N	3.74	23.29	21.91
GSRF + RxGS	1	3.57	22.47	21.12
WRF-GS+	N	5.84	25.81	21.84
WRF-GS+ + RxGS	1	6.17	24.27	20.55

Lower BLE error
For RF-3DGS and GSRF

Fewer outliers
Two WRF-GS+ outliers removed

Small gap elsewhere
0.8 to 1.7 dB on RFID, WiFi

Means over 21 BLE, 21 RFID, and 8 WiFi receivers. MAE in dBm, PSNR and SNR in dB.

Cost at N = 21 Receivers

One shared model and a multi-receiver rasterizer replace N per-receiver models.

45×

faster training (up to)

7.6×

faster inference (up to)

24×

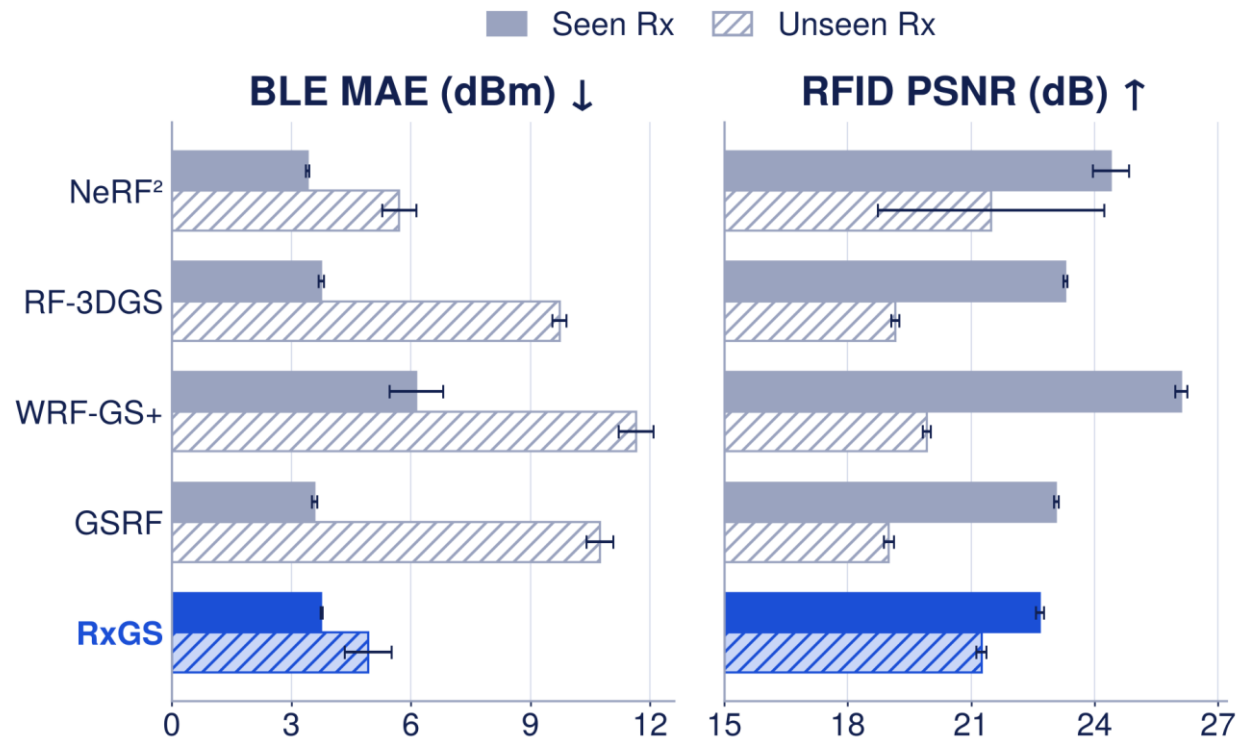
smaller storage (up to)

RFID	Train (h)	Infer (ms)	Storage (MB)
NeRF ²	14.3	2436.4	2.6
GRaF	16.2	59891.4	143.7
RF-3DGS	2.8	156.4	181.9
RF-3DGS + RxGS	0.4 (7×)	35.3 (4.4×)	8.8 (21×)
GSRF	5.5	238.1	548.0
GSRF + RxGS	0.6 (9×)	31.2 (7.6×)	26.1 (21×)
WRF-GS+	13.6	52.4	75.6
WRF-GS+ + RxGS	0.3 (45×)	42.5 (1.2×)	3.2 (24×)

Inference renders all 21 receivers per transmitter on one H100 GPU.

Generalization to Unseen Receivers

Train on 14 of 21 receivers in 3 folds, then test on all 21.



4.92

dBm unseen BLE MAE, lowest

9.7 to 11.6

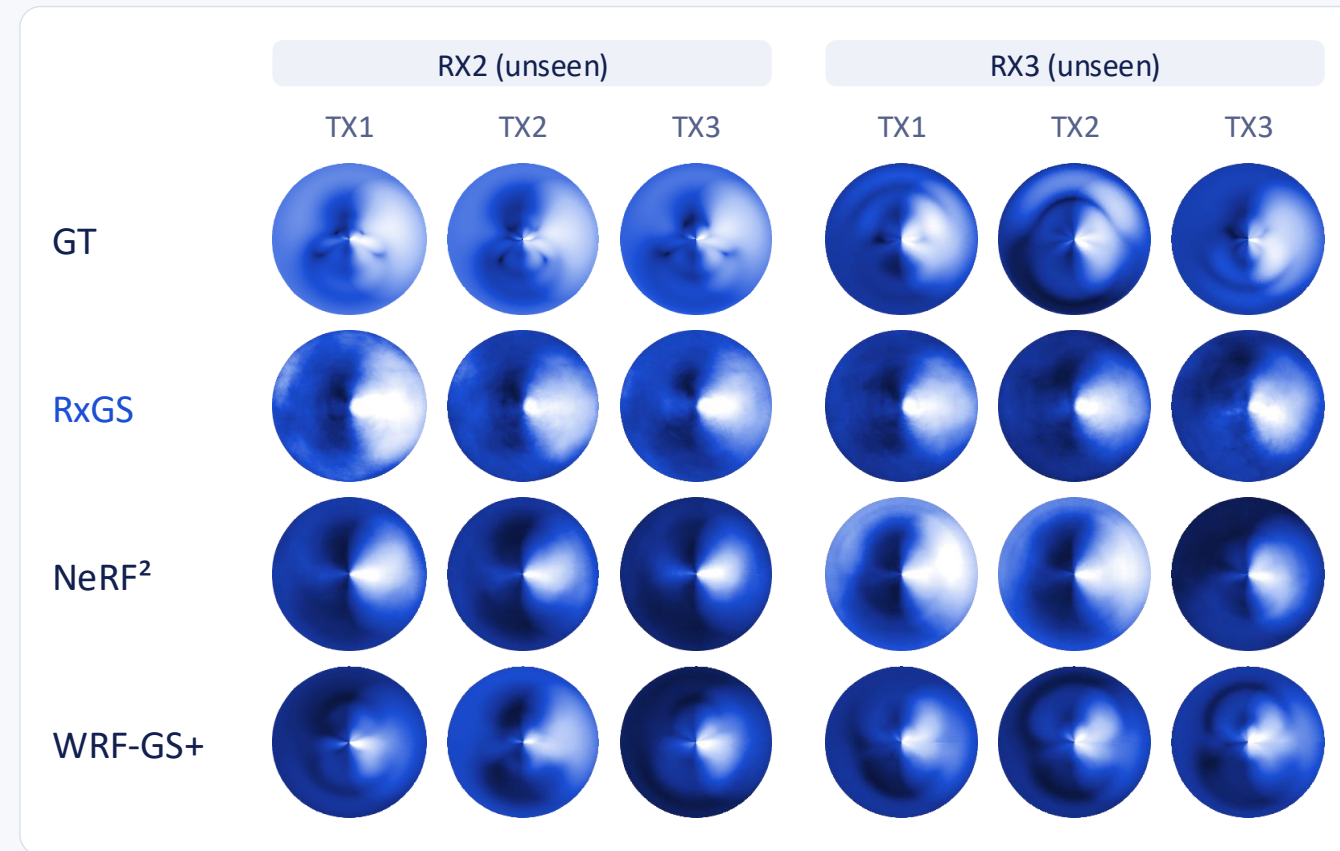
dBm, per-receiver baselines

21.25

dB unseen RFID PSNR

Spectra at Unseen Receivers

RX2 and RX3 are excluded from training. Brighter means stronger power.



RxGS

Sharp peaks at the right angles

NeRF²

Blurred peaks

WRF-GS+

Shifted peaks

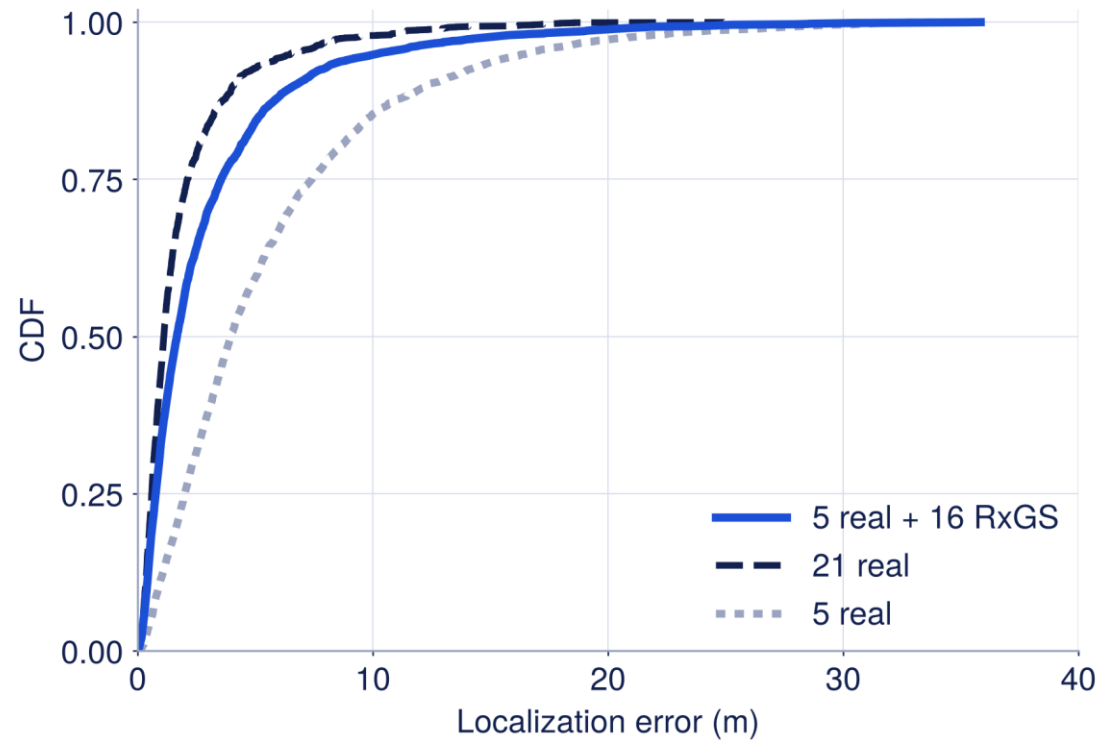
Ablation on BLE RSSI

Each row changes one design choice. MAE in dBm, lower is better.



Application: Sparse BLE Localization

16 virtual gateways from RxGS cut error by 47%, closing 71% of the gap.



5.61 m

5 real gateways

2.98 m

5 real + 16 RxGS

1.91 m

21 real gateways

Takeaways

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One model for every receiver in a scene.

- 1 One shared 3DGS model serves all fixed receivers.
- 2 It predicts receivers excluded from training.
- 3 Up to 45× faster training and 24× smaller storage.

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