

GVKF: Gaussian Voxel Kernel Functions for Highly Efficient Surface Reconstruction in Open Scenes

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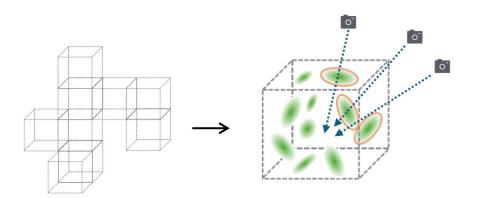


Method	Characteristic	Pros	Cons		
3DGS	Explicit		 High Mem Consumption 		
	Discrete	 Fast Rendering 	 Hard to Fit Continuous 		
	Alpha Blending		Surface		
INR	Implicit				
	Continuous	 Better Continuous Surface Fitting 	 Low Rendering Speed due to 		
	Volume Rendering	Mem Efficient	Dense Sampling		

We propose GVKF:

- ✓ Representing Continuous Surface
- ✓ High Rendering Speed, w/o Volume Rendering
- ✓ Implicit, Memory Efficient

NEURAL INFORMATION Method 1. Implicit Gaussian Representation



• Gaussian Attributes are stored in sparse voxel grids as 1D latent code \mathcal{F}

$$\mathcal{G}(x) = \alpha \cdot e^{-\frac{1}{2}(x-p)^T \sum^{-1} (x-p)}$$

• Attributes are decoded by several MLPs conditioned on 1D latent code

$$\alpha = \mathrm{MLP}_{\alpha}(\mathcal{F}, \mathrm{camera}), R = \mathrm{MLP}_{R}(\mathcal{F}), s = \mathrm{MLP}_{s}(\mathcal{F}), c = \mathrm{MLP}_{c}(\mathcal{F}, \mathrm{camera}).$$



• 3DGS are transformed to 1D Gaussian functions along the camera ray to evaluate the influence of opacity

$$t_i = \frac{p^T \Sigma^{-1} v}{v^T \Sigma^{-1} v}$$

• Alpha blending (Equivalent to 3DGS Rendering):

RAL INFORMATION

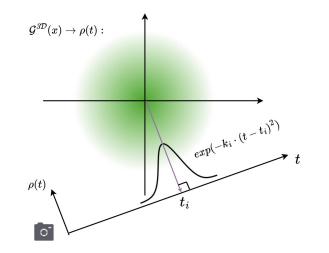
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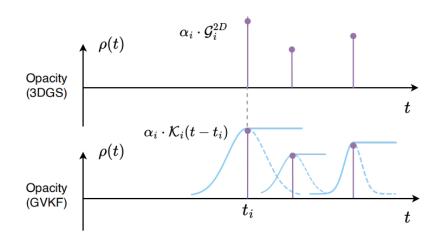
3DGS:
$$C = \sum_{i=1}^{N} c_i \cdot \alpha_i \cdot \mathcal{G}_i^{2D} \prod_{j=1}^{i-1} (1 - \alpha_j \cdot \mathcal{G}_j^{2D})$$

GVKF:
$$C = \sum_{i=1}^{N} c_i \cdot \alpha_i \cdot \mathcal{K}_i(0) \prod_{j=1}^{i-1} (1 - \alpha_j \cdot \mathcal{K}_j(0))$$

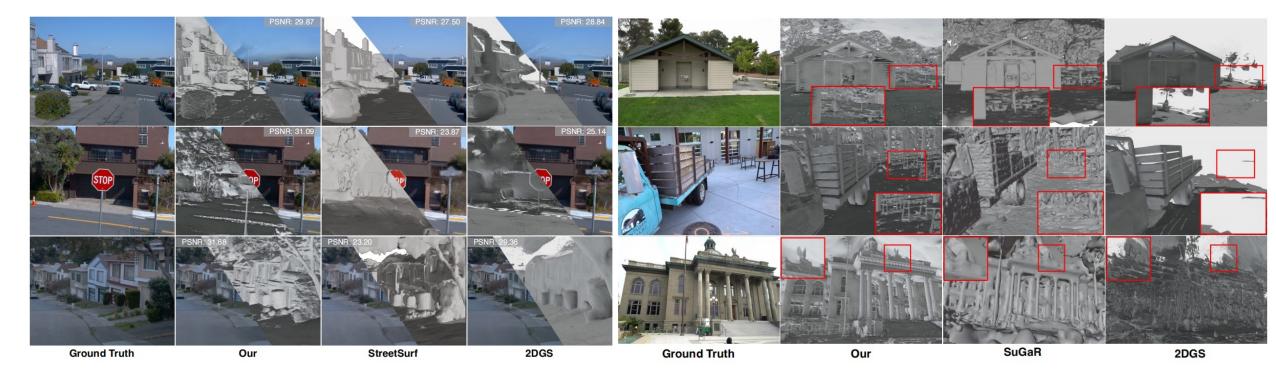
• Surface Representation (CDF of kernel functions):

$$\Phi(t) = \sum_{i=1}^{N} \alpha_i \cdot \mathcal{K}_i(t-t_i) \prod_{j=1}^{i-1} (1-\alpha_j \cdot \mathcal{K}_j(t-t_j))$$









Method	$PSNR \uparrow$	$\text{C-D}\downarrow$	MB (Storage) \downarrow	$\text{GB}\left(\text{GPU}\right) \downarrow$	$FPS \uparrow$	Training Time \downarrow
NeuS	13.24	0.76	170	31	~ 0.1	5 h
F ² -NeRF	24.70	886.77	130	24	~ 0.1	0.8 h
StreetSurf	27.12	1.02	540	22	~ 0.1	1.5 h
3DGS	27.99	3.57	230	23	63	0.75 h
SuGaR	23.71	3.08	228	33	56	1.5 h
2DGS	28.51	1.67	238	23	51	0.7 h
GVKF (Ours)	30.24	1.57	30	14	32	1.5 h

Method	Implicit			Explicit			
incentou	NeuS	Geo-NeuS	Neuralangelo	SuGaR	3DGS	2DGS	Ours
Barn	0.29	0.33	0.70	0.14	0.13	0.36	0.40
Caterpillar	0.29	0.26	0.36	0.16	0.08	0.23	0.34
Courthouse	0.17	0.12	0.28	0.08	0.09	0.13	0.25
Ignatius	0.83	0.72	0.89	0.33	0.04	0.44	0.51
Meetingroom	0.24	0.20	0.32	0.15	0.01	0.16	0.23
Truck	0.45	0.45	0.48	0.26	0.19	0.26	0.40
Mean	0.38	0.35	0.50	0.19	0.09	0.30	0.36
Time	>24 h	>24 h	>24 h	>1 h	${\sim}15~min$	$\sim \! 30 \min$	${\sim}1.5~h$

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Thanks !

Project page: <u>https://3dagentworld.github.io/gvkf/</u>

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