

# DC-Gaussian: Improving 3D Gaussian Splatting for Reflective Dash Cam Videos

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# 3DGS on dash cam videos is untapped.

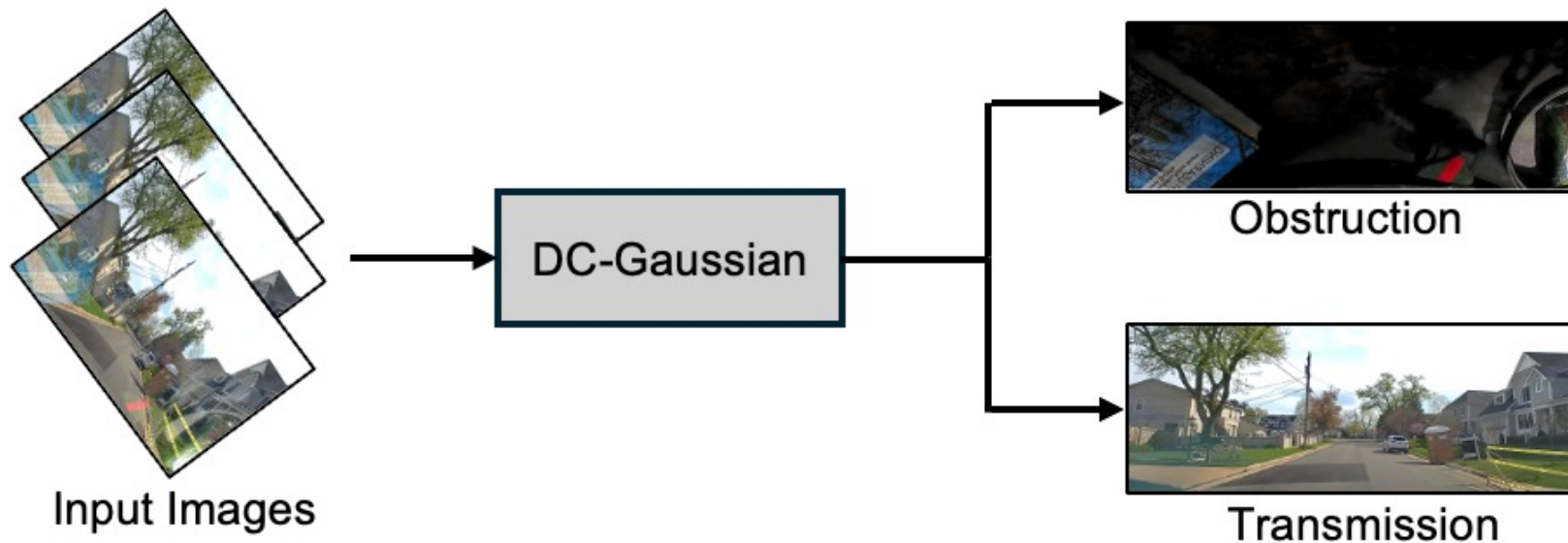
- The advance of neural rendering techniques opens up new possibilities in autonomous driving.
- Existing methods are primarily designed for videos collected by autonomous cars.
- Dash cam videos deeply reflect the diversity and complexity of real-world traffic scenarios.

# Applying 3DGS on dash cam videos is challenging.

- Existing obstruction removal methods fall short on the **complex obstructions** on windshield.
- Naively training 3DGS on dash cam videos faces strong **ambiguity** between obstructions and driving scenes.
- **Varying illumination** in real world makes this task even more challenging.



# Our Task: Novel View Synthesis and Obstruction Removal



- **Novel view synthesis:** synthesizing images at novel view perspectives.

- **Obstruction removal:** removing obstructions by decomposing the images.

# Observations

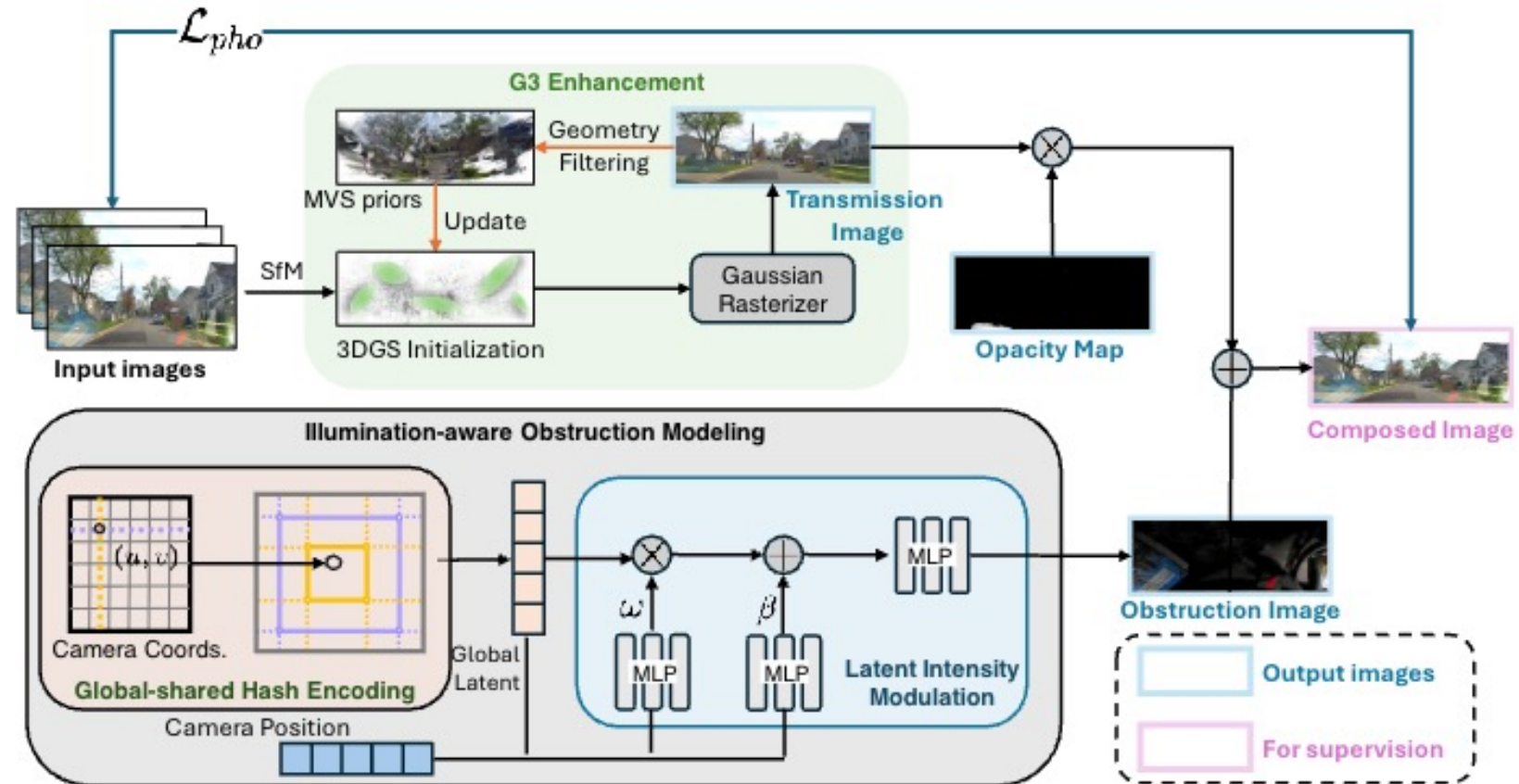


➤ **Observation 1** Reflections are from objects inside the car. Reflections and occlusions are both relatively **stationary** with the car.

➤ **Observation 2** The strength of reflections are conditioned on the incident light, which is **changing** as cars move along the road.

# Pipeline

- **Global-shared Hash Encoding** utilizes the static motion prior of obstructions.
- **Latent Intensity Modulation** grasps the intensity changes of reflections.
- **MVS priors** is leveraged to enhance the geometry of 3D Gaussians.

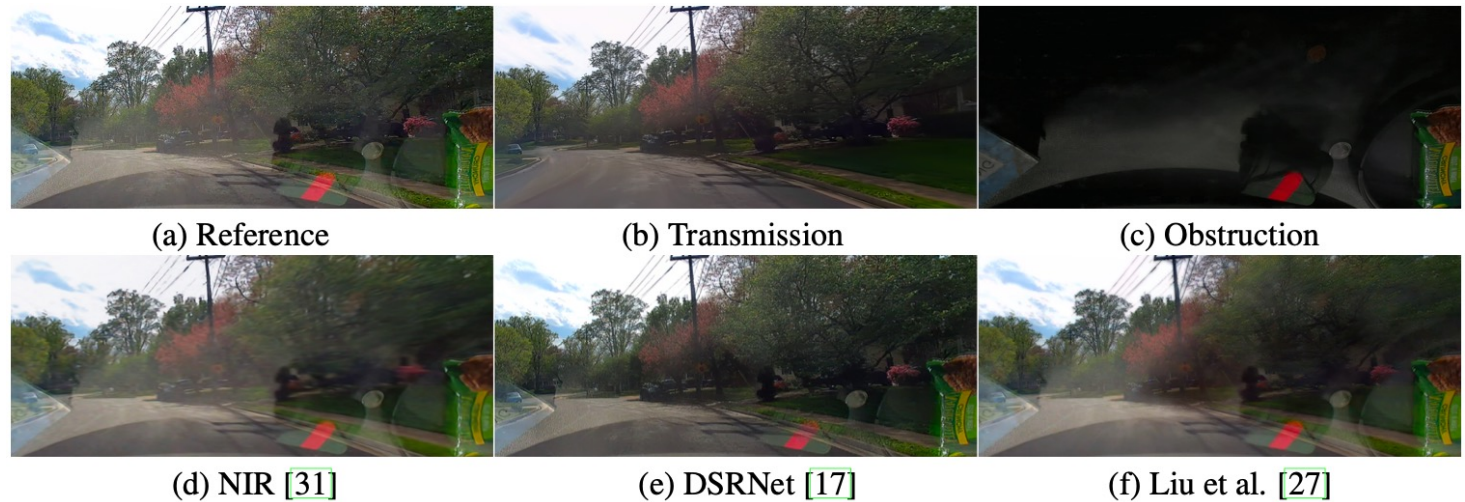


# Qualitative Results

➤ Our method surpasses 3DGS in both rendering quality and geometry.



➤ Our method achieves significantly better results in obstruction removal.



# Quantitative Results

Table 1: Evaluation of novel view synthesis on BDD100K and DCVR. We indicate the best and second best with bold and underlined respectively. Our method consistently outperforms state-of-the-art methods in both datasets and all the evaluation metrics.

Method	BDD100K			DCVR		
	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
ZipNeRF [4]	27.89	0.875	0.176	<u>24.41</u>	<u>0.786</u>	<u>0.228</u>
GaussianPro [9]	27.75	0.894	0.192	23.71	0.770	0.270
3DGS [19]	<u>28.02</u>	<u>0.897</u>	<u>0.188</u>	23.73	0.783	0.248
DCGaussian (Ours)	<b>29.44</b>	<b>0.914</b>	<b>0.143</b>	<b>24.74</b>	<b>0.822</b>	<b>0.202</b>

Table 2: Ablations studies on DCVR. Metrics are calculated on obstruction influenced areas.

NOM	AD	LIM	G3E	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
$\times$	$\times$	$\times$	$\times$	23.99	0.738	0.287
$\checkmark$	$\times$	$\times$	$\times$	25.21	0.776	0.252
$\checkmark$	$\checkmark$	$\times$	$\times$	25.65	0.791	0.236
$\checkmark$	$\checkmark$	$\checkmark$	$\times$	25.90	0.798	0.229
$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	<b>26.30</b>	<b>0.814</b>	<b>0.210</b>