

# Not All Frame Features Are Equal: Video-to-4D Generation via Decoupling Dynamic-Static Features

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# Motivation

- Existing methods directly optimize Gaussians using **whole information in frames**.
- If the **static regions** account for a large proportion in frames, existing methods often overlook information in dynamic regions and are prone to **overfitting on static regions**. This leads to producing results with blurry textures.

# Motivation

- We think **decoupling dynamic-static features** can solve this problem.

(a)

	<b>Only Static Region (A)</b>	<b>A Large Proportion of Static Region (B)</b>	<b>Only Dynamic Region (C)</b>
Description of Motion in Video	The person merely stands still <u>without</u> any movement.	The person exhibits a <u>slight swaying motion</u> at the waist.	The person undergoes a <u>rapid</u> downward movement.
Input Video			
Previous Work			
Ours w/o TSSF			
Ours			

(b) Reference frame (R)  
Frame at time  $i$  (C)



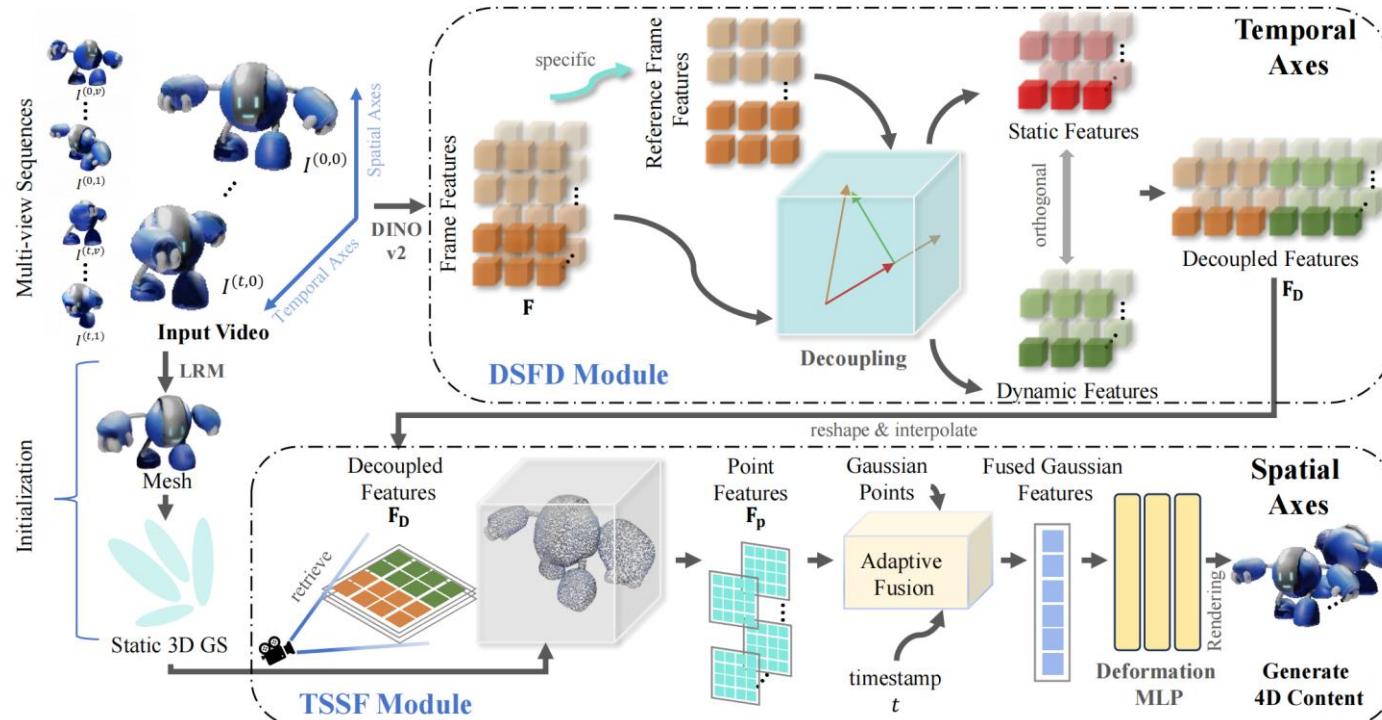
Dynamic Features



R: Reference frame  
C: Current frame

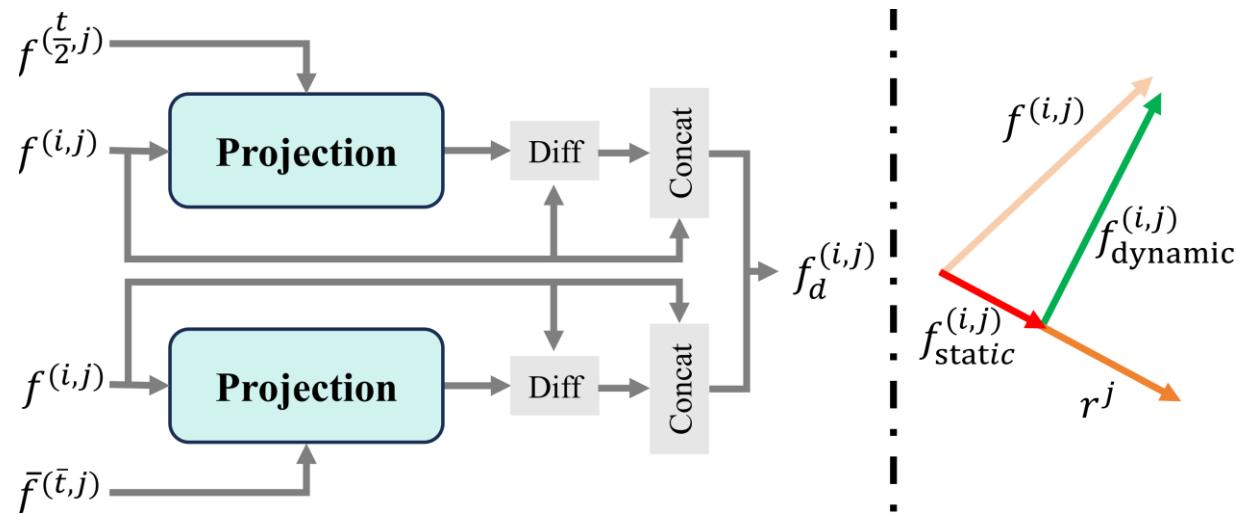
# Methodology

- **Dynamic-static feature decoupling module (DSFD):** Along temporal axes, it regards the regions of current frame features that possess significant differences relative to reference frame features as dynamic features.
- **Temporal-spatial similarity fusion module (TSSF):** Along spatial axes, it adaptively selects similar information of dynamic regions.



# Core of Decoupling

- We observe that regions with larger semantic magnitudes across time tend to exhibit higher semantic consistency, **while dynamic regions often yield smaller projection values** due to variations in object pose and position. Thus, **orthogonal projection** is applied between two frame features to decouple.



# Comparisons with Existing Methods

- The best score is highlighted in bold. For a fair comparison, the experiment of 4Diffusion and L4GM on Objaverse dataset are disregarded since they are inference-based methods trained on this dataset.

Methods	Optimization	Consistent4D dataset				Objaverse dataset			
		CLIP ↑	LPIPS ↓	FVD ↓	FID-VID ↓	CLIP ↑	LPIPS ↓	FVD ↓	FID-VID ↓
Consistent4D	✓	0.9085	0.1316	1041.2242	28.6471	0.8491	0.2222	1814.5652	48.7921
Dreamgaussian4D	✓	0.9145	0.1517	844.9087	37.9977	0.8127	0.2017	1545.3009	58.3686
STAG4D	✓	0.9078	0.1354	986.8271	26.3705	0.8790	0.1811	1061.3582	30.1359
SC4D	✓	0.9117	0.1370	852.9816	26.4779	0.8490	0.1852	1067.7582	40.5130
4Diffusion	✗	0.8734	0.2284	1551.6363	149.6170	-	-	-	-
L4GM	✗	0.9158	0.1497	898.0604	31.4996	-	-	-	-
DS4D-GA (Ours)	✓	0.9206	0.1311	799.9367	26.1794	0.8868	0.1761	890.2646	26.6717
DS4D-DA (Ours)	✓	<b>0.9225</b>	<b>0.1309</b>	<b>784.0235</b>	<b>24.0492</b>	<b>0.8881</b>	<b>0.1759</b>	<b>870.9489</b>	<b>25.3836</b>

# Comparisons with Existing Methods

Input Video

STAG4D  
(ECCV24)

L4GM  
(NeurIPS24)

DS4D-GA (Ours)

DS4D-DA (Ours)



Due to previous works overfitting on static regions, they easily generate unsatisfactory results.



Our methods **are the first to** decouple dynamic-static information in frames along temporal-spatial axes for mitigating such issues.



# Application: Dynamic Scene Render

**Ours**

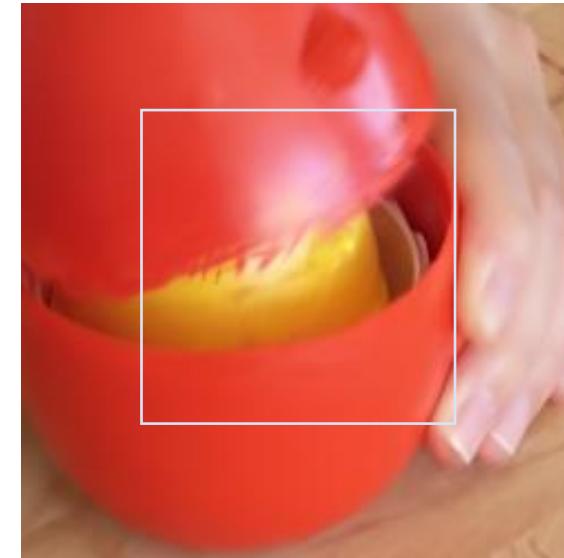


**GT**



**PSNR:**

**4D-GS**

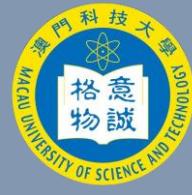


**27.88**

**Ours**



**29.54**



# Thank you for tuning in!

