











VideoRoPE

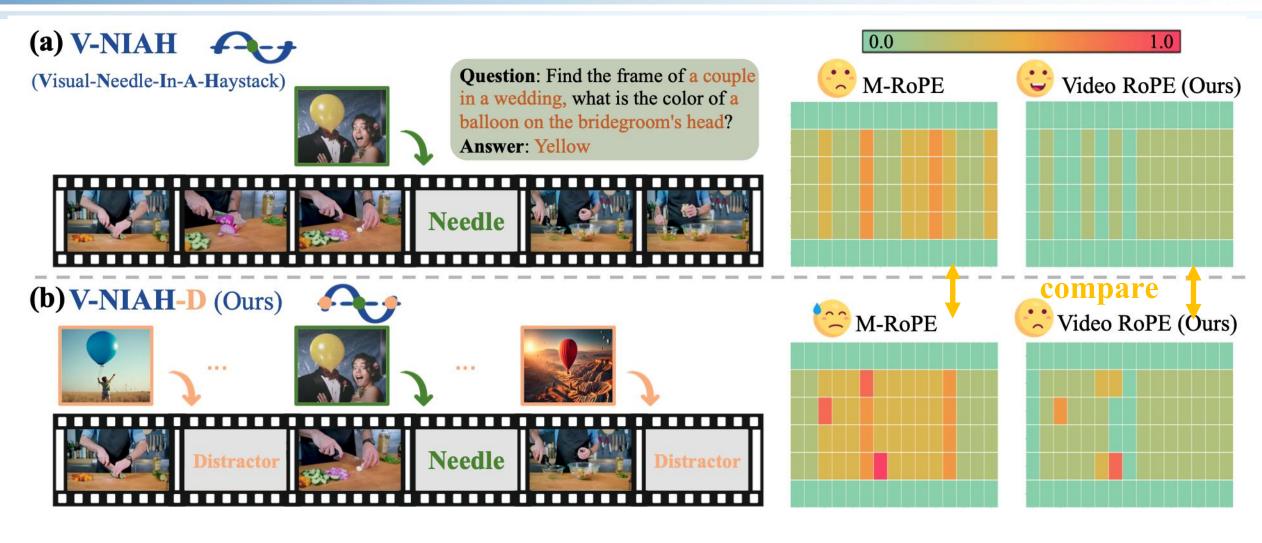
What Makes for Good Video Rotary Position Embedding?

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Observation 1

Interference Issues in Modern RoPE Variants





Current advanced position embedding methods, such as M-RoPE, are still susceptible to periodic distractor interference (V-NIAH-D).

Observation 2

Misfocused Attention Sink



haystack



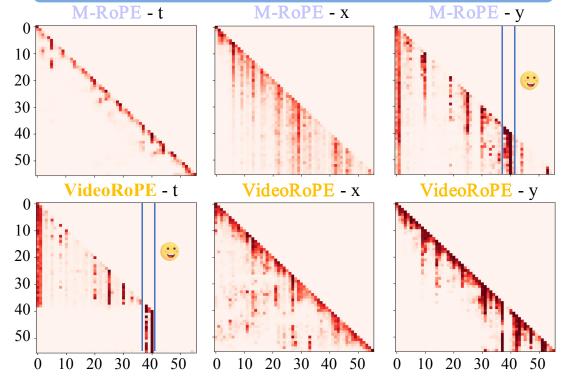




Question: what is being transferred to the beaker in the laboratory?

A. Solid substance B. Gas C. Nothing D. Liquid tester

M-RoPE: A. Solid substance VideoRoPE: D. Liquid tester :



- Both M-RoPE and VideoRoPE successfully locate the needle information required to answer the question.
- Due to suboptimal frequency allocation, M-RoPE focuses on vertical cues at the expense of temporal semantics, leading to poor long-range modeling and wrong answers. VideoRoPE, by leveraging temporal localization, answers correctly.

Four Key Properties



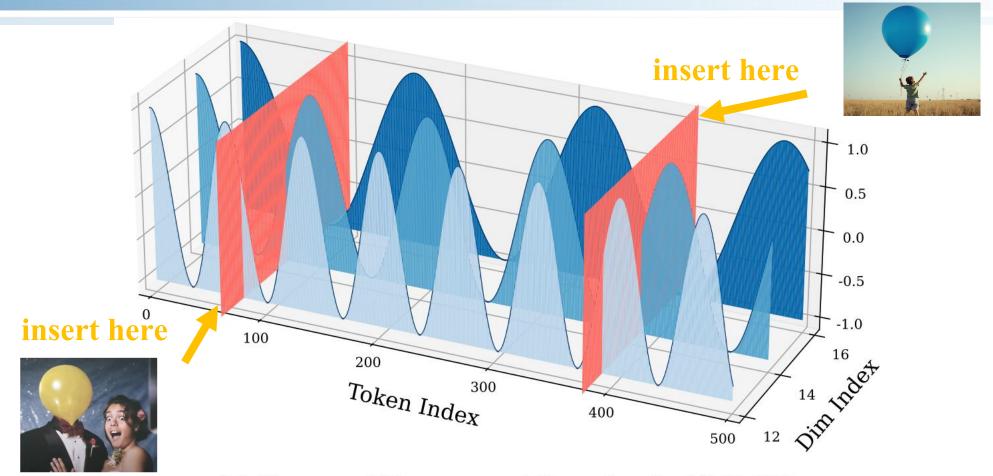
- most previous methods only cover **part of** the table
- VideoRoPE achieves a full-stack design, addressing all four core dimensions: structural modeling, frequency allocation, spatial symmetry, and temporal scaling—surpassing prior RoPE variants.



	2D/3D Structure	Frequency Allocation	Spatial Symmetry		poral al Scaling try	Temporal Index Scaling
Vanilla Re	oPE (Su et al	., 2024)	X	X	X	X
TAD-RoP	E (Gao et al.	, 2024)	X	X	X	1
RoPE-Tie	(Su, 2024a)		1	X	1	X
M-RoPE	(Wang et al.,	2024a)	✓	X	X	X
VideoRoP	E (Ours)		1	1	1	✓

Low-frequency Temporal Allocation (LTA)



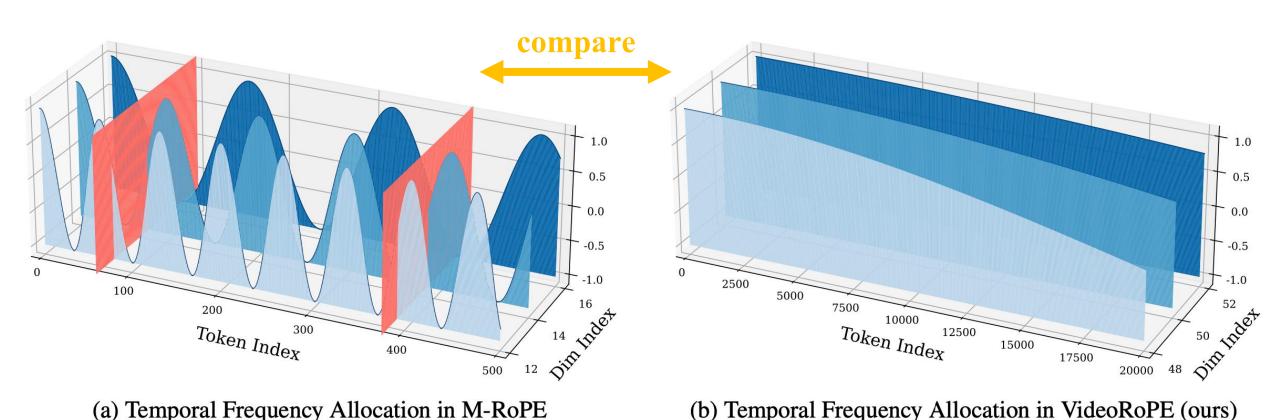


(a) Temporal Frequency Allocation in M-RoPE

As shown in the red planes, positions that are far apart in time can end up with **similar** positional encodings due to these **oscillations**.

Low-frequency Temporal Allocation (LTA)

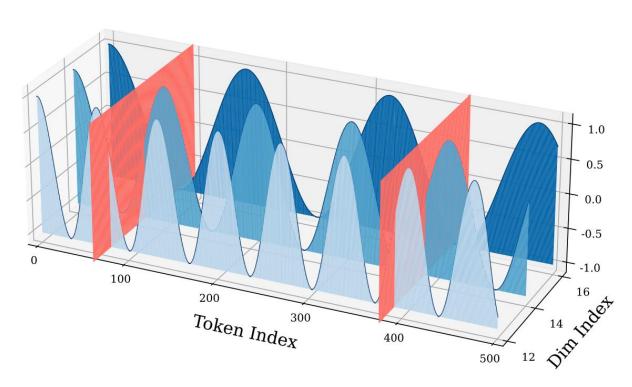




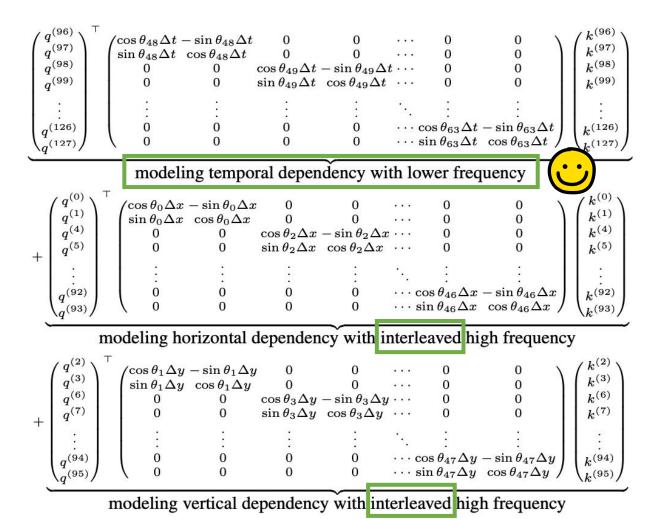
VideoRoPE adopts low-frequency modeling for the temporal dimension, achieving better long-range monotonicity and avoiding oscillations, which effectively reduces distractor interference in V-NIAH-D.

Low-frequency Temporal Allocation (LTA)



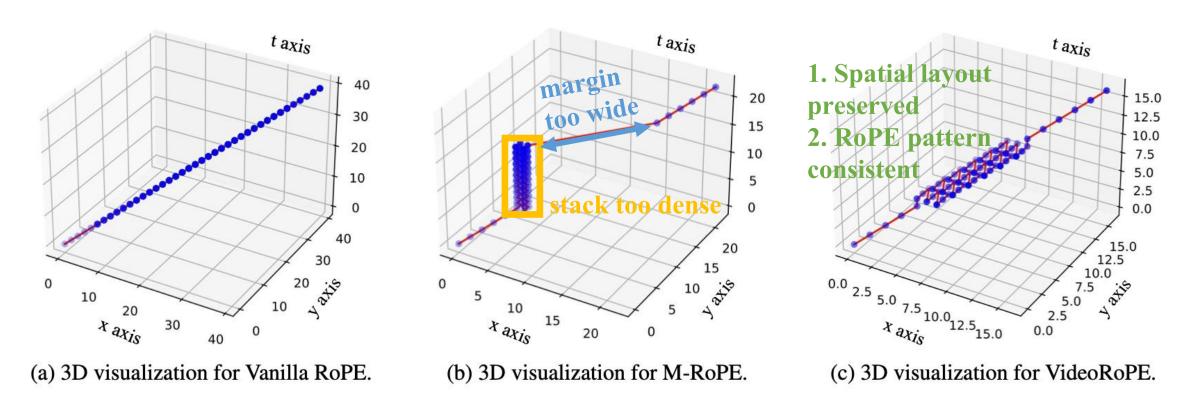


(a) Temporal Frequency Allocation in M-RoPE



Diagonal Layout (DL)





3D visualization of position embeddings: (a) Vanilla RoPE lacks spatial modeling. (b) M-RoPE introduces inconsistent index growth across frames. (c) VideoRoPE balances spatial modeling with consistent indexing, preserving RoPE's desirable structure.

Adjustable Temporal Spacing (ATS)



$$(t, x, y) = \begin{cases} (\tau, \tau, \tau) & \text{if } 0 \leq \tau < T_s \\ \left(\begin{array}{c} T_s + \delta(\tau - T_s), \\ T_s + \delta(\tau - T_s) + w - \frac{W}{2}, \\ T_s + \delta(\tau - T_s) + h - \frac{H}{2} \end{array} \right) & \text{if } T_s \leq \tau < T_s + T_v \\ \left(\begin{array}{c} \tau + (\delta - 1)T_v, \\ \tau + (\delta - 1)T_v, \\ \tau + (\delta - 1)T_v \end{array} \right) & \text{if } T_s + T_v \leq \tau < T_s + T_v + T_e \end{cases}$$

A djustable Temporal Spacing(ATS). To scale the temporal index, we introduce a scaling factor δ to better align temporal information between visual and textual tokens.

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Experiments on Long Video Understanding

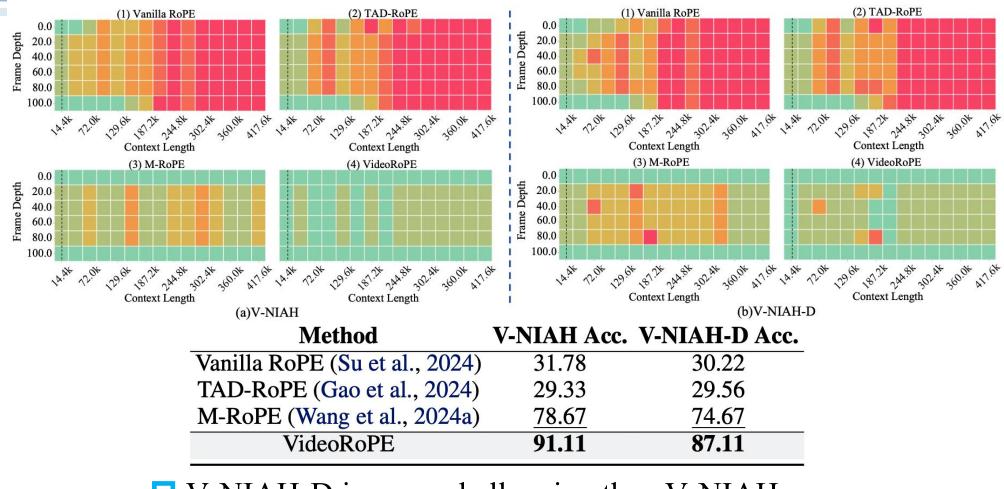


Method	LongVideoBench			MLVU				Video-MME				
	8k	16k	32k	64k	8k	16k	32k	64k	8k	16k	32k	64k
Vanilla RoPE (Su et al., 2024)	54.97	54.87	54.56	54.04	63.31	65.79	65.93	62.02	60.67	60.00	61.33	58.33
TAD-RoPE (Gao et al., 2024)	54.14	<u>55.08</u>	53.94	53.42	63.67	65.28	65.28	60.73	60.33	61.33	62.00	58.67
M-RoPE (Wang et al., 2024a)	53.42	52.80	53.11	54.35	60.41	60.68	61.56	61.10	60.67	59.67	61.00	59.67
VideoRoPE (Ours)	<u>54.46</u>	55.29	57.15	57.26	65.19	66.29	66.02	65.56	61.33	61.00	61.67	61.33

- Benchmarks: LongVideoBench, MLVU, VideoMME
- Consistent gains over M-RoPE: +2.91 / +4.46 / +1.66 @64k context
- Robust to long-range dependencies
- Strong adaptability across tasks

Experiments on Long Video Retrieval





- □ V-NIAH-D is more challenging than V-NIAH
- Vanilla RoPE / TAD-RoPE: limited extrapolation
- □ VideoRoPE > M-RoPE in long context extrapolation
- □ +12.44% over M-RoPE on Video Retrieval

Experiments on Video Hallucination



Method		11.000	SD			
Vanilla RoPE (Su et al., 2024)	<u>51.5</u>	30.0	48.0	8.0	43.0	36.1
TAD-RoPE (Gao et al., 2024)	51.0	37.0	<u>48.0</u>	11.5	<u>47.5</u>	39.0
M-RoPE (Wang et al., 2024a)	39.0	29.0	43.5	<u>12.5</u>	<u>47.5</u>	34.3
VideoRoPE	57.0	58.5	50.5	15.0	50.0	46.2

- □ +29.5% on Temporal Hallucination → better temporal reasoning
- □ +18.0% on Spatial/Object-Relation Hallucination → better spatial understanding
- Robust to complex video hallucinations

Experiments on Ablation Studues



Method	L	ongVid	leoBenc	h	MLVU				
	8k	16k	32k	64k	8k	16k	32k	64k	
Baseline	53.42	52.80	53.11	54.35	60.41	60.68	61.56	61.10	
+ DL	52.17	52.07	53.31	53.63	62.06	63.03	62.52	62.75	
+ DL & LTA	54.46	55.49	54.66	55.60	63.35	64.09	64.00	63.26	
+ DL & LTA & ATS	54.46	55.29	57.15	57.26	65.19	66.29	66.02	65.56	

- □ Ablation on LongVideoBench & MLVU (64k context)
- Baseline (M-RoPE): 54.35 / 61.10
- \square +DL \rightarrow +LTA \rightarrow +ATS \rightarrow performance improves progressively
- ☐ Final: 57.26 / 65.56
- ☐ Effective use of spatio-temporal position encoding

^{*} Further ablations on layout strategies, frequency allocation, ATS scaling, and DL are provided in the main paper.

Conclusion



□ Four key criteria for effective positional encoding: □ 2D/3D structure, frequency allocation, spatial symmetry, temporal index scaling ☐ Prior RoPE variants struggle with **temporal distractors due to** improper allocation □ VideoRoPE addresses this with: □ 3D spatiotemporal structure □ Low-frequency temporal allocation (reduces oscillations) Diagonal spatial layout (ensures symmetry) ☐ Adjustable temporal spacing (ATS) **□** Superior performance in: Long video retrieval ☐ Video understanding □ Video hallucination tasks



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