VLA-Cache: Efficient Vision-Language-Action Manipulation via Adaptive Token Caching

NVIDIA GTC 2026

NEURAL INFORMATION PROCESSING SYSTEMS
NeurIPS 2025

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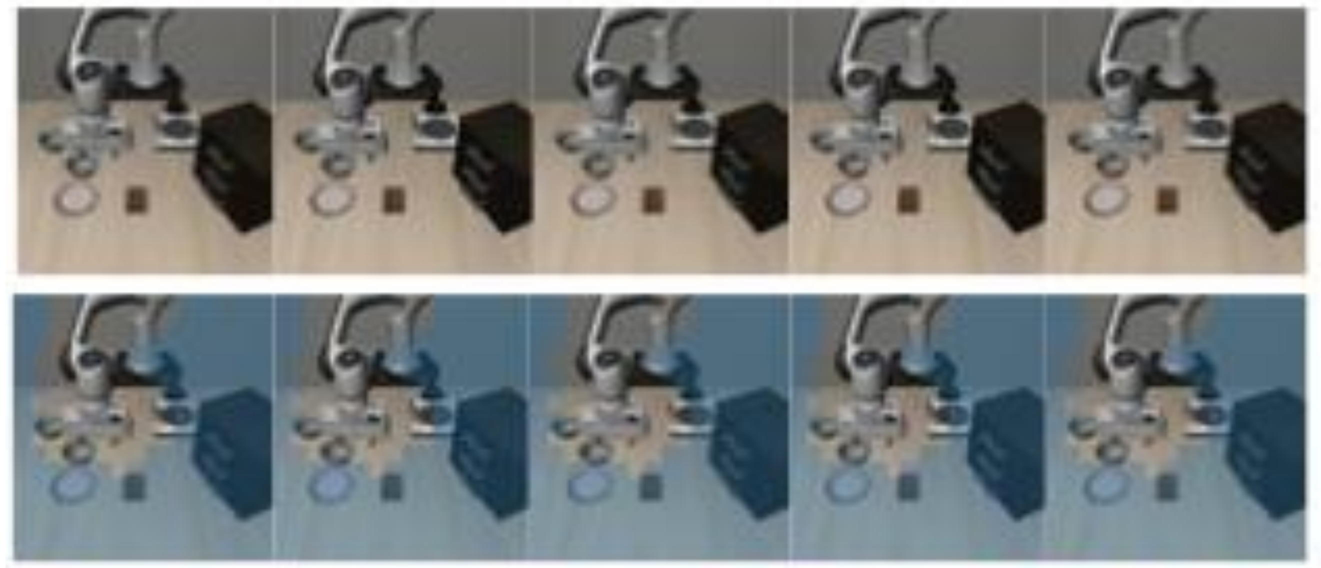
A training-free method for real-time acceleration in Vision-Language-Action models

Motivation

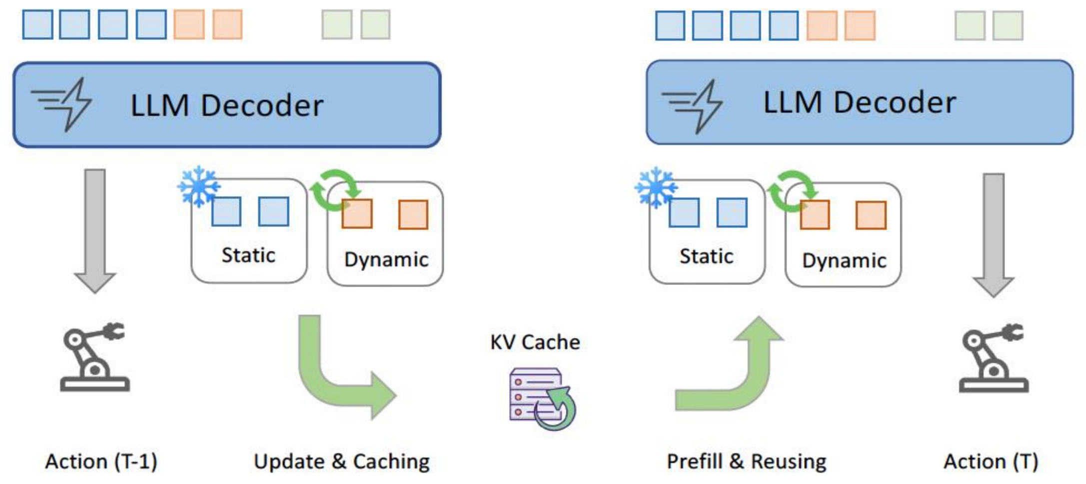
- **V**ision-**L**anguage-**A**ction models enable generalizable robotic manipulation.
- **High computational cost** in robotic VLA inference limits real-time control.
- Many visual tokens remain static across frames yet are redundantly processed.



Key insight: Instead of re-encoding all visual tokens per frame, we can reuse information that remains unchanged.

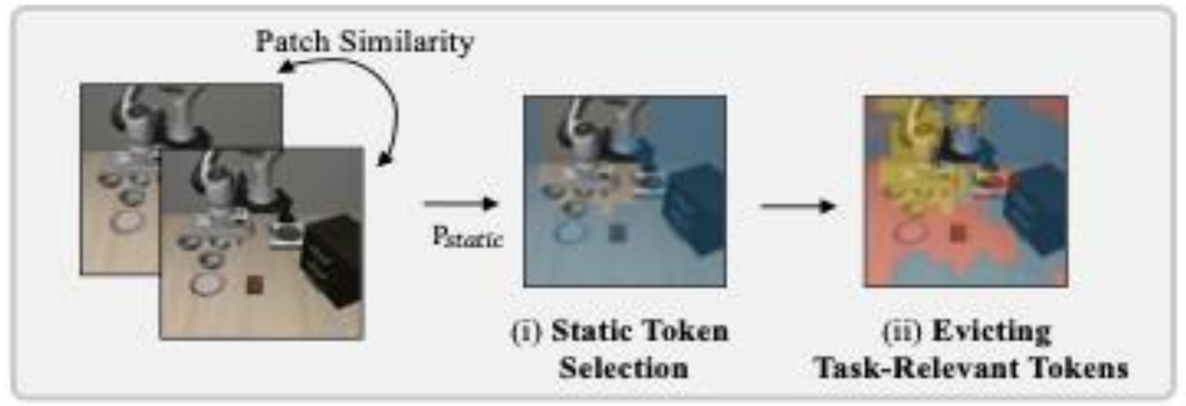
Contributions

- **VLA-Cache** provides a training-free caching method for real-time robotic control.
- Reuses static tokens for faster, accurate inference.
- Experiments show **1.7× faster latency** and **15% higher control frequency** with no performance loss.



Dynamic Token Selection

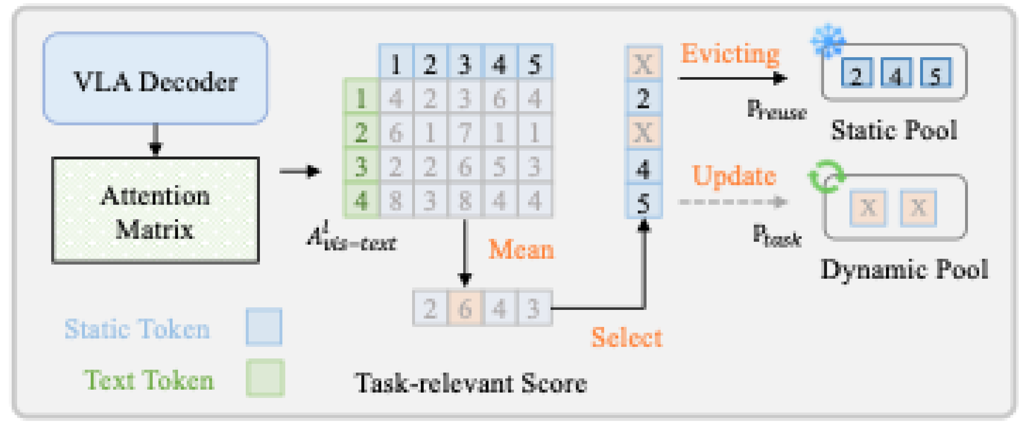
- **Static-token caching:** identifies visually unchanged patches cross frames and caches them for reuse.
- **Task-relevant filtering:** uses cross-attention scores from the language decoder to remove semantically critical regions.

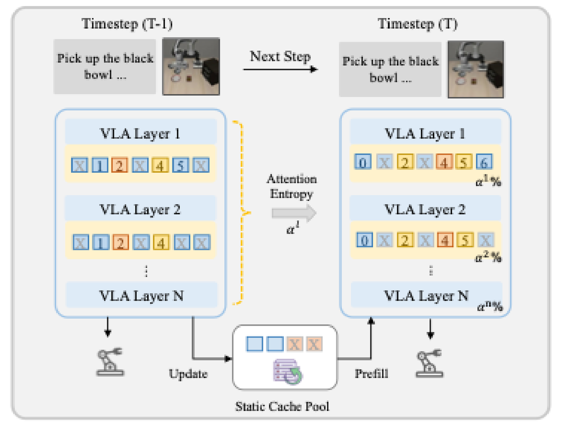


"Reuse what's redundant, recompute what matters."

Adaptive Token Caching

- Attention patterns differ across decoder layers.
- Layers with more concentrated attention reuse more tokens.
- **Layer-adaptive reuse** balances efficiency and fidelity.





Module-wise Performance Gains

- Static-token caching reduces latency but harms success rate.
- Task-relevant filtering restores accuracy.
- Layer-adaptive reuse achieving the best overall performance.

Method	SR (%) ↑	Latency (ms) ↓
OpenVLA	84.4	51.56
+ Static Token	74.2	31.03
+ Evict Task-Relevant	82.6	31.03
+ Layer Adaptive	83.8	32.22

Takeaway: static caching accelerates, filtering safeguards accuracy, and layer-adaptive reuse achieves optimal balance.

Simulation Results

Evaluations on the **LIBERO** and **SIMPLER** benchmarks show that VLA-Cache consistently accelerates VLA inference while maintaining comparable or higher success rates.

LIBERO

Method	Success Rate ↑					FLOPs (T)↓	Latency (ms)↓	Control Freq. (Hz)↑
	Spatial	Object	Goal	Long	Average			
OpenVLA	84.4%	86.6%	75.6%	53.2%	75.0%	1.864	51.91	4.23
+ SparseVLM	79.8%	67.0%	72.6%	39.4%	64.7%	1.407	83.39	3.72
+ FastV	83.4%	84.0%	74.2%	51.6%	73.3%	1.864	53.28	4.19
+ **VLA-Cache**	**83.8%**	**85.8%**	**76.4%**	**52.8%**	**74.7%**	**1.355**	**31.83**	**4.59**
OpenVLA-OFT	97.8%	97.6%	97.6%	94.2%	96.8%	4.013	79.05	65.10
+ **VLA-Cache**	**98.3%**	97.5%	**98.3%**	**95.4%**	**97.4%**	**3.097**	**62.59**	**78.98**

SIMPLER

SIMPLER	Method	Success Rate ↑					FLOPs (T)↓	Latency (ms) ↓	Control Freq. (Hz) ↑
		PickCan	MoveNear	Drawer	DrawerApple	Average			
Matching	CogACT	91.3%	**85.0%**	**71.8%**	50.9%	**74.8%**	1.847	54.29	12.42
	+ **VLA-Cache**	**92.0%**	83.3%	70.5%	**51.6%**	74.4%	**1.496**	**39.63**	**14.66**
Aggregation	CogACT	89.6%	80.8%	28.3%	**46.6%**	61.3%	1.807	53.54	12.36
	+ **VLA-Cache**	**91.7%**	**79.3%**	**32.5%**	45.8%	**62.3%**	**1.493**	**39.11**	**14.48**

VLA-Cache achieves 1.7× lower latency and improved control frequency without retraining.

Real-world Results

On real-robot manipulation tasks with OpenVLA, VLA-Cache transfers effectively from simulation to reality.

Method	Success Rate ↑					FLOPs (T)↓	Latency (ms) ↓	Control Freq. (Hz) ↑
	PickPot	PlaceCube	PutSausage	WipeTable	Average			
OpenVLA	**95.0%**	83.3%	80.0%	70.0%	82.1%	1.814	64.16	4.02
+ **VLA-Cache**	90.0%	**90.0%**	**85.0%**	**73.3%**	**84.6%**	**1.303**	**51.85**	**4.21**

Dynamic Viewpoint & Scene

VLA-Cache remains robust under **camera motion** and **dynamic scene changes**, enabling reliable inference from wrist-mounted views and complex real-time environments.

Dynamic Scene

Wrist Camera