

VLA-Cache: Towards Efficient Vision-Language-Action Model via Adaptive Token Caching in Robotic Manipulation

Siyu Xu¹ Yunke Wang¹ Chenghao Xia¹ Dihao Zhu¹ Tao Huang¹ Chang Xu¹

Abstract

Vision-Language-Action (VLA) model can process instructions and visual perception to directly generate actions as output in an end-to-end fashion due to its strong multi-modal reasoning capabilities. While the performance of VLA models is promising, their computational cost can be substantial. This raises challenge for applying them on robotics tasks, which requires real-time decision-making to respond quickly to environmental changes. Since robotic control involves sequential decision-making, the visual input often exhibits minimal variation between successive steps. A natural idea is to reuse the computational results of unchanged visual tokens from the last step. Motivated by this idea, we propose VLA-Cache, an efficient vision-language-action model. VLA-Cache incorporates a token-selection mechanism that compares the visual input at each step with the input from the previous step, adaptively identifying visual tokens with minimal changes. The computational results for these unchanged tokens are then reused in subsequent steps via KV-cache, thereby significantly improving the efficiency of the VLA-Cache model. Experimental results on both simulation (*e.g.*, LIBERO benchmark and SIMPLER) and real-world robot validate VLA-Cache can achieve practical acceleration with minimal sacrifice in success rate.

1. Introduction

Learning a robust and generalizable policy for robotic manipulation through policy learning has long been a challenging problem (Kim et al., 2020), with traditional reinforcement learning approaches (Choi et al., 2024; Bica et al., 2021) often suffering from poor robustness and limited generalization. Recently, the rapid advancement of foundational Vision-Language Models (VLMs) (Awadalla et al.,

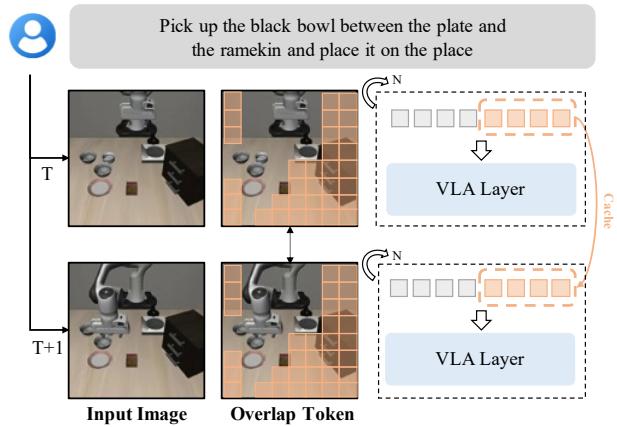


Figure 1. During the inference of the VLA model, static tokens of the input image remain largely consistent across steps. This consistency allows for caching the computations of these tokens from the previous step and improving the efficiency of inference.

2023; Liu et al., 2024b) has demonstrated remarkable capabilities in multimodal understanding and generalization. Leveraging large-scale real-world robotic datasets (O’Neill et al., 2024; Fang et al., 2024), pioneering works (Zitkovich et al., 2023; Octo Model Team et al., 2024; Niu et al., 2024; Kim et al., 2024) have introduced Vision-Language-Action (VLA) models, which integrate vision and language modalities to directly generate robotic actions in an end-to-end manner. This emerging paradigm holds great promise for enhancing the adaptability and generalization of robotic control systems, but leaves a large computational demand.

To mitigate the extensive cost of VLA models, existing works often adopt generic acceleration techniques, such as model lightweighting (Wen et al., 2024), quantization (Park et al., 2024), and early exit (Yue et al., 2024). However, these approaches fail to account for the unique characteristics of VLA models, leading to suboptimal efficiency gains and limited performance improvements.

In this paper, we argue that robotic manipulation, characterized by sequential action-scene interactions, inherently prioritizes visual inputs related to the robotic arm and the target object, while the background remains largely static and less critical. As illustrated in Figure 1, the static tokens of the input image remain largely consistent across steps.

¹School of Computer Science, University of Sydney, Sydney, Australia. Correspondence to: Chang Xu <c.xu@sydney.edu.au>.

In this context, the background tokens, which contribute significantly to computational overhead and repeat across sequential steps in the VLA process, are often redundant.

As a result, we propose **VLA-Cache**, a novel approach that identifies and reuses static tokens across sequential VLA steps. Specifically, static tokens in each step refer to visual tokens that exhibit minor changes compared to the previous step. Instead of recomputing these tokens, VLA-Cache directly substitutes them with their cached representations from the preceding step, significantly reducing redundant computations and improving inference efficiency. Nevertheless, we observe that model precision is highly sensitive to task-relevant tokens (*i.e.*, those related to the robotic arm and the target object) in the ablation study, where even a slight positional shift can lead to a significant performance drop. To address this, we introduce a fine-grained selection scheme that filters out task-relevant tokens from the static token set, ensuring that these critical tokens continue to undergo full computational interactions, thereby preserving model accuracy while maintaining efficiency.

Additionally, based on the observation that attention distributions within the VLA decoder vary significantly across different layers, we propose a layer-adaptive strategy that adjusts the fraction of reused tokens based on each layer’s attention concentration. We evaluate VLA-Cache on a diverse set of robotic manipulation tasks in the LIBERO benchmark, where it demonstrates over $1.7\times$ acceleration compared to the baseline, with only slight drop on the success rate. Furthermore, VLA-Cache is deployed on the Kinova Jaco robot arm, showing that it can achieve practical acceleration in real-world scenarios.

2. Related Work

Vision-Language-Action Models. Large-scale vision-language models (VLMs) have significantly advanced multimodal learning by integrating image understanding and language reasoning (Liu et al., 2024b; Bai et al., 2023). Extending these capabilities, Vision-Language-Action (VLA) models (Zitkovich et al., 2023; Li et al., 2023) incorporate an action modality, enabling end-to-end visuomotor control. These models typically adopt large VLM backbones (Touvron et al., 2023) and fine-tune them on robot data (O’Neill et al., 2024), with approaches varying from discretizing actions as language-like tokens (Kim et al., 2024; Chi et al., 2023) to incorporating specialized diffusion policy heads (Black et al., 2024). Despite their effectiveness in tasks like object retrieval and assembly (Huang et al., 2024; Zhao et al., 2023), VLA models demand substantial computation, making real-time deployment challenging, particularly in resource-constrained environments.

Acceleration for Vision-Language Models. Acceler-

ation techniques for VLMs, such as quantization (Xie et al., 2024) and pruning (Lin et al., 2024a), have shown success in vision-language tasks but often overlook the real-time demands of action generation. Token-level methods like FastV (Chen et al., 2025) and SparseVLM (Zhang et al., 2024) optimize inference by pruning or merging redundant tokens, but their effectiveness in VLA tasks, which require short and highly specialized action sequences, remains unclear. Some works address efficiency by modifying VLA architectures, such as DeeR-VLA (Yue et al., 2024), which dynamically adjusts inference depth, and QAIL (Park et al., 2024), which integrates quantization-aware training. Others, like RoboMamba (Liu et al., 2024c) and TinyVLA (Wen et al., 2024), focus on replacing traditional attention mechanisms or training compact models from scratch, often requiring re-training and additional data collection. In contrast, VLA-Cache offers a training-free acceleration approach by selectively caching static tokens and recomputing only dynamic or task-relevant ones, preserving crucial temporal cues while reducing inference latency and improving real-time robotic control efficiency.

3. Preliminary

3.1. Vision-Language-Action Models

Vision-Language-Action (VLA) models extend large-scale VLMs to generate robotic actions based on multimodal inputs, including visual observations and task instructions. These models are typically trained on large-scale datasets, such as Open X Embodiment (O’Neill et al., 2024), which contains over a million real-world robot trajectories. The training pipeline involves a pre-trained vision encoder (Liu et al., 2021; Radford et al., 2021) extracting image features, which are projected into the input space of a Large Language Model (LLM). The LLM, fine-tuned alongside a projector module, encodes these inputs to predict actions.

During inference, VLA models process sequential frames to iteratively guide the robot, but the full Transformer-based LLM inference at each step results in substantial computational overhead. The quadratic complexity of self-attention, combined with large key-value (KV) caches (Ge et al., 2023), leads to high memory consumption and slow inference speeds, posing challenges for real-time deployment. While model compression techniques such as quantization (Lin et al., 2024b) and pruning (Park et al., 2024; Yue et al., 2024) have been explored to reduce computational cost, they typically require re-training and may degrade performance, limiting their practicality in real-time applications. To mitigate these inefficiencies, our approach leverages token caching mechanisms to accelerate inference in a training-free manner, reducing computational cost while preserving inference accuracy.

3.2. Key-Value Caching in Transformer Models

Key-Value (KV) caching is a well-established optimization in autoregressive Transformers (Vaswani, 2017; Floridi & Chiriatti, 2020), allowing previously computed key (\mathbf{K}) and value (\mathbf{V}) representations to be stored and reused in subsequent timesteps. Given input tokens \mathbf{X} , self-attention first projects them into queries, keys, and values:

$$\mathbf{Q} = \mathbf{X}W_Q, \quad \mathbf{K} = \mathbf{X}W_K, \quad \mathbf{V} = \mathbf{X}W_V. \quad (1)$$

The attention output is computed as:

$$\text{Attn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{D}}\right)\mathbf{V}. \quad (2)$$

In standard inference, new keys and values are appended to the cache:

$$\mathbf{K}_t = \text{Concat}(\mathbf{K}_{t-1}, \mathbf{K}_{\text{new}}), \quad \mathbf{V}_t = \text{Concat}(\mathbf{V}_{t-1}, \mathbf{V}_{\text{new}}). \quad (3)$$

While this improves efficiency by avoiding redundant recomputation, it does not reduce memory or computational costs, as all tokens are still processed.

VLA-Cache extends this approach by introducing **dynamic token reuse**. Instead of appending all new tokens, it identifies static tokens across frames and skips their recomputation:

$$\mathbf{K}_t(i) = \begin{cases} \mathbf{K}_{t-1}(i), & i \in \mathcal{P}_{\text{reuse}}, \\ W_K \mathbf{H}_t(i), & \text{otherwise.} \end{cases} \quad (4)$$

$$\mathbf{V}_t(i) = \begin{cases} \mathbf{V}_{t-1}(i), & i \in \mathcal{P}_{\text{reuse}}, \\ W_V \mathbf{H}_t(i), & \text{otherwise.} \end{cases} \quad (5)$$

where $\mathcal{P}_{\text{reuse}}$ represents the subset of tokens that remain visually and semantically unchanged between frames. By selectively updating only task-relevant tokens, VLA-Cache significantly reduces redundant computation while preserving high-fidelity action predictions.

This caching mechanism integrates seamlessly into the Transformer decoding process, requiring no architectural modifications or additional training. The following sections detail the implementation of VLA-Cache and its effectiveness in improving inference efficiency for VLA models.

4. Methodology

In robotic action prediction, consecutive image frames often show only minor changes in the manipulator or target objects, while the background remains mostly unchanged. This motivates us to reuse some of unchanged tokens in the last step to accelerate the inference at current step. However, the choice of reusing tokens should be made very carefully, as even small changes to the manipulator or target objects

can be pivotal for accurate action prediction. Treating such tokens as static could severely degrade performance. Consequently, the core challenge in accelerating VLA inference via token caching lies in accurately distinguishing genuinely static regions from those that are dynamic or closely tied to the task. By automatically detecting static tokens across consecutive frames and discarding those related to the manipulator or the immediate task, one can realize substantial computational savings while still preserving high-quality action predictions.

4.1. Dynamic Token Selection

Static Token Selection. To enhance inference efficiency, we identify visually static tokens across consecutive frames and reuse their associated Key-Value (KV) representations. This process involves three steps: partitioning the input image into patches, computing patch-wise similarity, and selecting the most static patches for reuse.

Given an image I of size $H \times W$, we divide it into $N \times N$ non-overlapping patches of size $p \times p$, yielding N^2 patches $\mathcal{P} = \{\mathbf{P}_{i,j}\}$. Each patch $\mathbf{P}_{i,j}$ is directly represented by its raw pixel values, without additional feature encoding.

For two consecutive frames I_t and I_{t-1} , we calculate the cosine similarity between their corresponding patches:

$$\text{Sim}(\mathbf{P}_t^{i,j}, \mathbf{P}_{t-1}^{i,j}) = \frac{\mathbf{P}_t^{i,j} \cdot \mathbf{P}_{t-1}^{i,j}}{\|\mathbf{P}_t^{i,j}\|_2 \|\mathbf{P}_{t-1}^{i,j}\|_2}. \quad (6)$$

A patch is considered static if its similarity score exceeds a predefined threshold τ . To further refine the selection, we apply a Top- k filter:

$$\mathcal{P}_{\text{top-}k} = \text{Top-}k\left(\{\mathbf{P}_t^{i,j} \mid \text{Sim}(\mathbf{P}_t^{i,j}, \mathbf{P}_{t-1}^{i,j}) \geq \tau\}\right). \quad (7)$$

Thus, patches with minimal visual variation are identified for reuse, while those displaying notable differences are recomputed. This approach accurately selects truly static tokens across consecutive frames, significantly reducing redundant computations and accelerating inference without compromising overall performance.

Evicting Task-Relevant Tokens. While many tokens remain visually static across consecutive frames, certain tokens that are highly relevant to the task (e.g., the gripper or the target object) cannot be directly reused. In our experiments, we observed that as the robotic arm approaches the target object, small but critical changes in the target region often occur. These changes are primarily caused by factors such as lighting variations or camera noise. Recomputing tokens around the target region before the gripper reaches it significantly improves task accuracy. To address this issue, we leverage the attention mechanism of the VLA model to identify task-relevant tokens in the next frame that require recalculation.

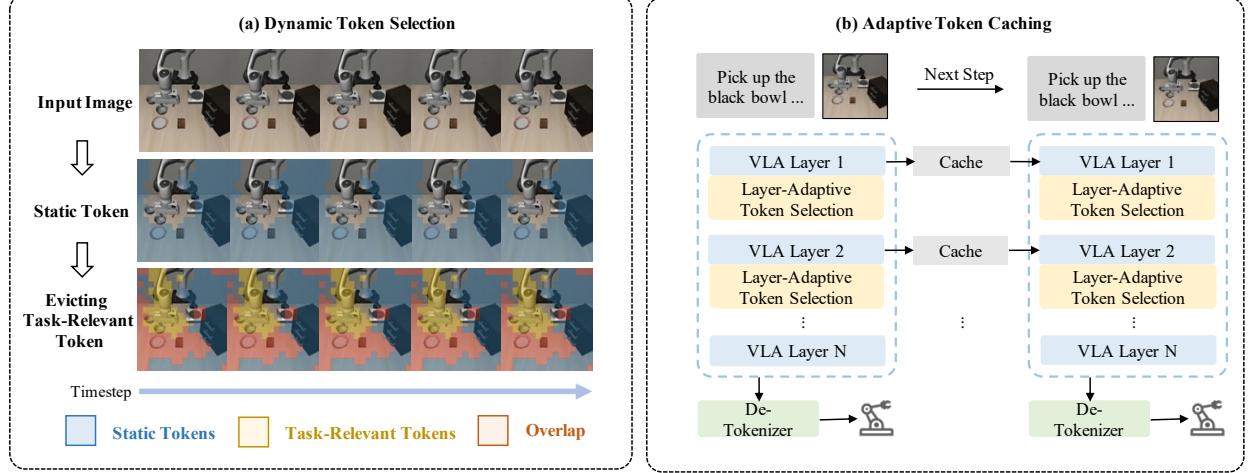


Figure 2. In this paper, we propose VLA-Cache, which includes two procedures. (a) Dynamic Token Selection: First, a static token set is identified, followed by filtering out task-relevant tokens to ensure critical information undergoes full computation. Tokens that remain in the set and overlap with those from the previous step will be retrieved from cache. (b) Adaptive Token Caching: The fraction of reused tokens is dynamically adjusted at each layer based on its attention distribution.

Specifically, we calculate the text-to-vision attention scores from the cross-attention module of the VLA model to determine the task relevance of each vision token. For each layer l , the attention weights are represented as $\mathbf{A}^l \in \mathbb{R}^{N_{\text{heads}} \times N_{\text{tokens}} \times N_{\text{tokens}}}$. From these weights, we extract the attention mapping from text tokens to vision tokens:

$$\mathbf{A}_{\text{vis-text}}^l = \mathbf{A}^l[:, v_{\text{start}} : v_{\text{end}}, t_{\text{start}} : t_{\text{end}}], \quad (8)$$

where $v_{\text{start}}, v_{\text{end}}$ and $t_{\text{start}}, t_{\text{end}}$ are the indices of the vision and text tokens, respectively.

To aggregate the attention scores across multiple heads, we compute the mean attention for each vision token as $\mathbf{A}_{\text{avg}}^l = \text{Mean}_{\text{heads}}(\mathbf{A}_{\text{vis-text}}^l)$. For task relevance across multiple layers \mathcal{L} , the final task relevance scores are obtained by averaging the scores across the selected layers as $\mathbf{S}_{\text{task-relevance}} = \text{Mean}_{l \in \mathcal{L}}(\mathbf{A}_{\text{avg}}^l)$.

Using these scores, we rank the vision tokens based on their task relevance and apply a threshold τ_{task} to select the most task-relevant tokens:

$$\mathcal{P}_{\text{task-relevant}} = \{\mathbf{P}_t^{i,j} \mid \mathbf{S}_{\text{task-relevance}}[i, j] \geq \tau_{\text{task}}\}. \quad (9)$$

Finally, we combine the set of static tokens $\mathcal{P}_{\text{static}}$ selected in the first step with the task-relevant tokens. Tokens that are both static and highly task-relevant are removed from the reusable token set to ensure they are recomputed in the current step:

$$\mathcal{P}_{\text{final}} = \mathcal{P}_{\text{static}} \setminus \mathcal{P}_{\text{task-relevant}}. \quad (10)$$

By filtering out high-attention tokens, this approach ensures that the VLA model accurately updates the critical objects

in the scene, thereby preventing failures caused by reusing outdated static tokens. This method effectively balances computational efficiency with task precision, enabling robust performance in robotic control tasks.

4.2. Layer Adaptive Token Reusing

While static token selection and task-relevance filtering eliminate a large portion of redundant computation, we observe that attention distributions within the VLA decoder vary significantly across different layers. This finding is consistent with observations reported by prior work *FastV* (Chen et al., 2025), indicating that both VLA and VLM decoders exhibit similar patterns of attention flow: early layers display dispersed attention, followed by fluctuations in intermediate layers, and eventually a partial rebound near the final layers.

To account for these differences, we propose a layer-adaptive strategy that adjusts the fraction of reused tokens based on each layer’s attention concentration. Specifically, we quantify the attention distribution at layer l via an *entropy* measure, following the same mean-attention computation described in equation 8. Let H^l denote the resulting entropy. We then define an *entropy ratio* R^l , which captures how much more concentrated the attention is in layer l compared to layer $l - 1$:

$$R^l = \frac{H^{l-1} - H^l}{H^{l-1}}. \quad (11)$$

A positive R^l indicates that the attention distribution at layer l is more focused than that of layer $l - 1$.

We accumulate these ratios across layers to obtain a cumulative score $R_{\text{cum}}^l = \sum_{j=1}^l R^j$, which in turn determines the

Algorithm 1 Adaptive Token Caching

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1: Input: Frames  $\{I_{t-1}, I_t\}$ , previous KV cache
    $\{\mathbf{K}_{t-1}^l, \mathbf{V}_{t-1}^l\}$ , thresholds  $\tau, \tau_{\text{task}}$ , hyperparameter  $k$ 
2: Output: Updated KV cache  $\{\mathbf{K}_t^l, \mathbf{V}_t^l\}$ 
3: Static Token Selection:
4: Patchify  $I_{t-1}, I_t$  and compute  $\text{Sim}(\mathbf{P}_t, \mathbf{P}_{t-1})$ 
5: Select  $\mathcal{P}_{\text{static}}$  where similarity  $\geq \tau$ 
6: Apply top- $k$  filtering to refine static token selection
7: Evict Task-Relevant Tokens:
8: Compute text-to-vision attention scores  $\mathbf{S}_{\text{task-relevance}}$ 
9: Select  $\mathcal{P}_{\text{task-relevant}}$  where attention  $\geq \tau_{\text{task}}$ 
10: Compute reusable tokens:  $\mathcal{P}_{\text{final}} = \mathcal{P}_{\text{static}} \setminus \mathcal{P}_{\text{task-relevant}}$ 
11: Layer-Adaptive Token Reuse:
12: Compute entropy reduction  $R^l, R_{\text{cum}}^l$ ; Determine reuse
   ratio  $\alpha^l$ ; Compute reusable subset  $\mathcal{P}_{\text{reuse}} \subseteq \mathcal{P}_{\text{final}}$ 
13: for each layer  $l$  and token  $i$  do
14:   if  $i \in \mathcal{P}_{\text{reuse}}$  then
15:     Reuse cached values:
          $\mathbf{K}_t^l(i) = \mathbf{K}_{t-1}^l(I), \mathbf{V}_t^l(i) = \mathbf{V}_{t-1}^l(i)$ 
16:   else
17:     Recompute:
          $\mathbf{K}_t^l(i) = W_K^l \mathbf{H}_t^l(i), \mathbf{V}_t^l(i) = W_V^l \mathbf{H}_t^l(i)$ 
18:   end if
19:   Compute self-attention:
20:    $\text{Attn}(\mathbf{Q}_t^l, \mathbf{K}_t^l, \mathbf{V}_t^l) = \text{Softmax}\left(\frac{\mathbf{Q}_t^l(\mathbf{K}_t^l)^{\top}}{\sqrt{D}}\right) \mathbf{V}_t^l$ 
21: end for
22: return Updated KV cache  $\{\mathbf{K}_t^l, \mathbf{V}_t^l\}$ 

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proportion α^l of static tokens (from $\mathcal{P}_{\text{final}}$) that are reused at layer l . Formally,

$$\alpha^l = \min\left(k \sum_{j=1}^l R^j, 1\right), \quad (12)$$

where k is a hyperparameter that governs the impact of attention concentration. Layers with larger cumulative entropy reduction are allowed to reuse a higher fraction of tokens, reflecting the insight that as attention becomes more focused, fewer tokens are likely to require recomputation.

In practice, this layer-adaptive mechanism dynamically adjusts token reuse based on the evolving attention patterns in the VLA decoder, effectively balancing computational efficiency with task accuracy. By selectively retaining only the most relevant tokens at each layer, our method significantly reduces redundant computations while maintaining reliable action prediction.

Inference with Cached Representation. During inference, VLA-Cache selectively caches and reuses previously computed representations to reduce redundant computations while maintaining accurate robotic action prediction. Instead of recomputing all tokens at each timestep, the model distinguishes between static and dynamic tokens. Static

tokens, which exhibit minimal visual change across consecutive frames, retain their cached key-value (KV) representations from the previous timestep, bypassing unnecessary computation. Dynamic tokens, which undergo significant changes or are task-relevant, are recomputed to ensure precise motion execution. This selective token reuse is performed at each layer, guided by entropy-based attention analysis to dynamically adjust reuse ratios. The full inference procedure, including static token selection, task-relevance filtering, and layer-adaptive token reuse, is outlined in Algorithm 1, with further details provided in Appendix A.2.

4.3. Theoretical Analysis of Computational Complexity

Computational Cost Reduction. In standard VLA inference, each Transformer layer processes L tokens, with a total FLOP cost per layer:

$$\text{FLOPs} \approx 4LD^2 + 2L^2D + 2LDM. \quad (13)$$

Our method reduces the effective token count per layer to $L_r = \alpha \times \mathcal{P}_{\text{final}}$, leading to theoretical savings:

$$\Delta \text{FLOPs}_{\text{layer}} \approx 4L_r D^2 + 2L_r^2 D + 2L_r DM. \quad (14)$$

These savings scale across multiple layers, significantly lowering computation while maintaining accuracy.

Overhead of Token Selection. The cost of static token identification is approximately $\mathcal{O}(H^2)$ due to patch similarity checks, while task-relevance filtering introduces a cross-modal attention aggregation cost of $\mathcal{O}(L_t L_v D)$. The entropy-based layer-adaptive strategy incurs an additional $\mathcal{O}(L^2 D)$ complexity, which remains significantly lower than the baseline per-layer cost.

Total Complexity Reduction. Bringing all components together, the theoretical overall FLOP reduction per layer is:

$$\begin{aligned} \Delta \text{FLOPs}_{\text{total}} \approx & \left(4L_r D^2 + 2L_r^2 D + 2L_r DM\right) \\ & - \left(H^2 + L_t L_v D + L^2 D\right). \end{aligned} \quad (15)$$

Further Derivations and Complexity Details. See Appendix A.1 for detailed derivations, including static token selection costs, attention filtering complexity, and layer-adaptive entropy calculations.

5. Experiment

5.1. Experimental Settings

To validate the generalization of VLA-Cache, we implement our method in both simulation and real-world settings. In simulation, we evaluate VLA-Cache on two open-source

VLA models: OpenVLA (Kim et al., 2024) and CogAct (Li et al., 2024a), using the LIBERO benchmark (Liu et al., 2024a) and SIMPLER environment (Li et al., 2024b), respectively. For fair comparison, we adopt two token-pruning acceleration methods, SparseVLM (Zhang et al., 2024) and FastV (Chen et al., 2025), as baselines in the LIBERO environment. OpenVLA processes 256 visual tokens per image, and all comparative experiments use an identical token pruning and reuse count, setting Top-K to 100 tokens.

For VLA-Cache, the default parameters are set as follows: similarity score threshold $\tau = 0.996$, top- $k = 100$, and task relevance threshold $\tau_{task} = 0.5$. Additionally, we use OpenVLA’s default caching mechanism and other default parameters for inference acceleration. In the SIMPLER environment, we apply VLA-Cache with the same parameter settings as OpenVLA while using CogAct’s default hyperparameters.

For real-world evaluation, we fine-tune OpenVLA for deployment on a Kinova Jaco2 6-DoF manipulator. The model is trained for 50,000 steps with default parameters. During testing, we modify only the similarity score threshold to $\tau = 0.85$, keeping all other parameters unchanged. All experiments are conducted on an NVIDIA RTX 4090 GPU.

5.1.1. LIBERO BENCHMARK

The LIBERO Benchmark (Liu et al., 2024a) is designed to evaluate lifelong robotic manipulation across four diverse task suites: LIBERO-Spatial, LIBERO-Object, LIBERO-Goal, and LIBERO-Long. Each suite introduces distinct variations in spatial layouts, object selection, task objectives, or long-horizon planning, challenging models to generalize across different manipulation scenarios.

Following the experimental setup of OpenVLA, we conduct evaluations on all four LIBERO suites, each containing ten subtasks. To ensure consistency, we use the same machine and official fine-tuned weights. For each subtask, multiple evaluation episodes are run, measuring key performance metrics such as success rate and inference latency. We evaluate VLA-Cache’s acceleration capabilities within the OpenVLA framework and conduct an ablation study on the top- k parameter in the LIBERO environment.

5.1.2. SIMPLER ENVIRONMENTS

The SIMPLER simulation environment (Li et al., 2024b) is designed to closely mirror real-world robotic setups, facilitating more realistic evaluations.

SIMPLER supports two evaluation settings: *Visual Matching* (aiming to minimize visual discrepancies between simulation and reality) and *Variant Aggregation* (building on Visual Matching by introducing variations in lighting, background, table textures, etc.). We adopt the same SIM-

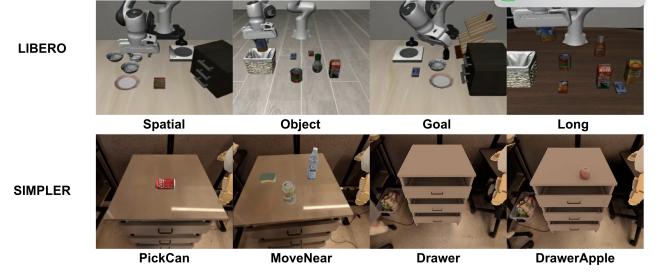


Figure 3. Simulation Tasks on LIBERO Benchmark and the SIMPLER Environment.

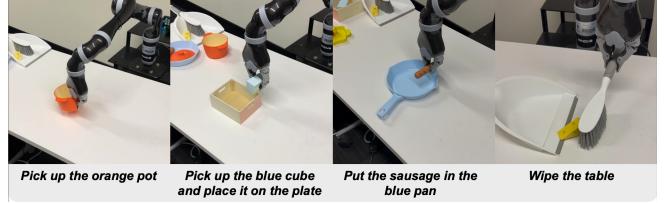


Figure 4. Robot Manipulation Tasks on Jaco2 Real-world Platform.

PLIER configuration used by CogAct and evaluate two settings, *Visual Matching* and *Variant Aggregation*, on a Google robot arm. Each setting contains four tasks: 1) *Pick coke can*(*PickCan*), 2) *Move near*(*MoveNear*), 3) *Open/close drawer*(*Drawer*), 4) *Open top drawer and place apple*(*DrawerApple*).

To validate the general applicability of our method, we use CogAct as the baseline model within the SIMPLER environment. CogAct extends OpenVLA by incorporating a Diffusion Policy head to predict actions in continuous space, a common strategy among recent VLA models. Similar to OpenVLA, CogAct provides publicly available weights and code for reproducible simulation-based evaluations. Through these experiments, we try to verify its potential as a general VLA acceleration technique.

5.1.3. REAL-WORLD ROBOT SETTING

We further evaluate our method on a Kinova Jaco2 6-DoF manipulator, equipped with a Sony AX53 camera positioned in front of the arm to capture the manipulation scene.

Tasks. We design four real-world robotic manipulation tasks: 1) *Pick up the orange pot* (*PickPot*), 2) *Place the blue cube in the box* (*PlaceCube*), 3) *Put the sausage in the blue pan* (*PutSausage*), 4) *Wipe the table* (*WipeTable*). For the wiping task, we place objects of various shapes and colors on the table to challenge the model’s robustness to unseen objects.

Data Collection. Using an Xbox Gamepad, we teleoperate the Jaco2 arm and collect demonstrations at a frequency of 10 Hz, recording RGB images and robot states throughout each trajectory. We gather 150–200 demonstrations per task

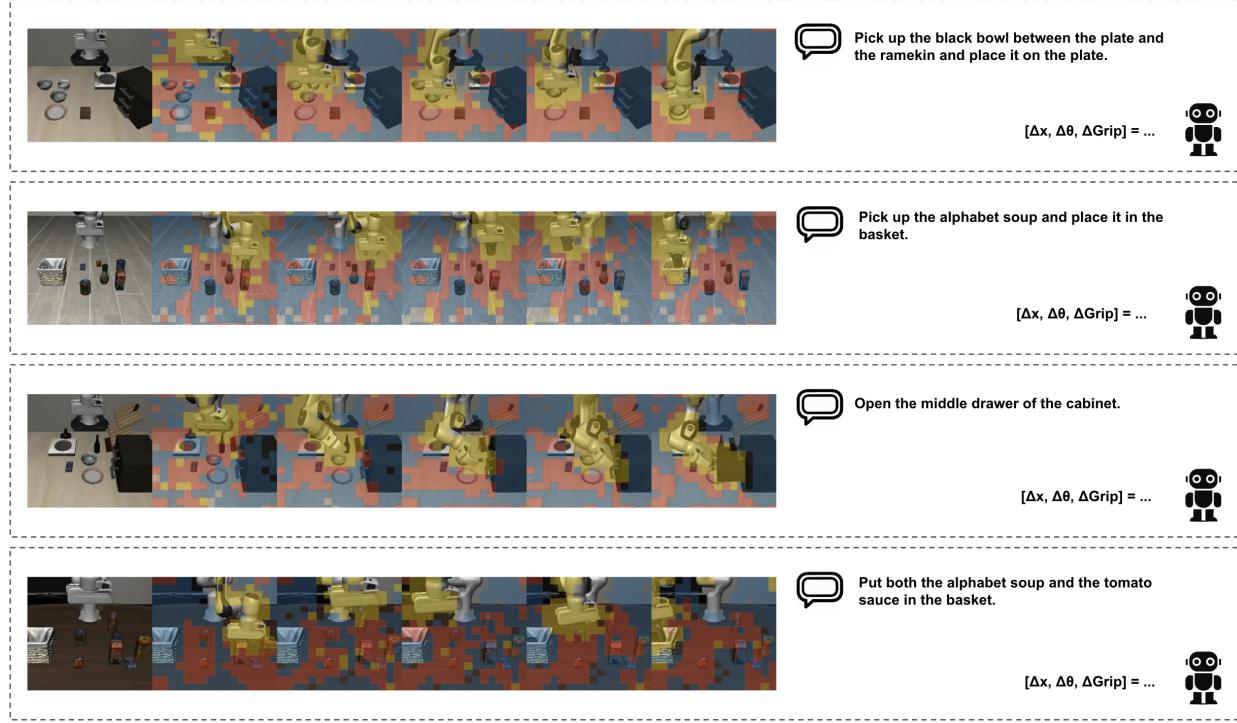


Figure 5. Heatmap Visualization of Robot Actions in a Simulated Environment with Prompt Descriptions and Outputs

Method	Success Rate ↑					FLOPS↓	CUDA Time(ms)↓
	LIBERO-Spatial	LIBERO-Object	LIBERO-Goal	LIBERO-Long	Average		
Baseline (OpenVLA)	84.4%	86.6%	75.6%	53.2%	75.0%	1.864	51.91
SparseVLM	79.8%	67.0%	72.6%	39.4%	64.7%	1.407	83.39
FastV	83.4%	84.0%	74.2%	51.6%	73.3%	1.864	53.28
VLA-Cache	83.8%	85.8%	76.4%	52.8%	74.7%	1.355	31.83

Table 1. Comparison of different VLA acceleration methods on the LIBERO benchmark.

SIMPLER	Method	Success Rate ↑					FLOPS↓	CUDA Time(ms)↓
		PickCan	MoveNear	Drawer	DrawerApple	Average		
Visual Matching	Baseline (CogACT)	91.3%	85.0%	71.8%	50.9%	74.8%	1.847	54.29
	VLA-Cache	92.0%	83.3%	70.5%	51.6%	74.4%	1.496	39.63
Variant Aggregation	Baseline (CogACT)	89.6%	80.8%	28.3%	46.6%	61.3%	1.807	53.54
	VLA-Cache	91.7%	79.3%	32.5%	45.8%	62.3%	1.493	39.11

Table 2. Comparison of VLA Cache in CogACT model within the SIMPLER environment.

to form the training dataset.

Baseline. We fine-tune OpenVLA via LoRA (Low-Rank Adaptation (Hu et al., 2021)) on each task and then deploy it on the Jaco2 to assess real-world performance. The finetuning process follows the same hyperparameter setup as in LIBERO.

5.2. Results on Simulation Environment

Main Results on LIBERO. Table 1 summarizes the success rate, FLOPs, and CUDA inference time across the four LIBERO task suites. Compared to the baseline, VLA-Cache

achieves a **27.31%** FLOPs reduction and a **1.63×** speedup, with only a minimal 0.3% drop in the overall success rate, confirming its efficiency without compromising accuracy. While VLA-Cache slightly underperforms on spatial, object, and long-horizon tasks, it notably surpasses the baseline on the goal suite, highlighting its robust adaptability.

Notably, both FastV and SparseVLM fail to improve inference time, often exceeding the baseline. FastV merely masks tokens in attention computation without reducing GPU workload, introducing additional masking overhead, while SparseVLM incurs extra cost from token pruning, merging, and recycling. These methods were originally de-

Method	Success Rate ↑					FLOPs↓	CUDA Time(ms)↓
	PickPot	PlaceCube	PutSausage	WipeTable	Average		
Baseline (OpenVLA)	95.0%	83.3%	80.0%	70.0%	82.1%	1.814	64.16
VLA-Cache	90.0%	90.0%	85.0%	73.0%	84.5%	1.303	51.85

Table 3. Comparison of success rate on real robot tasks.

Method	Success Rate ↑	FLOPs↓	CUDA Time(ms)↓
Static Token	74.2%	1.304	31.03
Task Relevant	82.6%	1.304	31.03
Layer Adaptive (Ours)	83.8%	1.382	32.22

Table 4. Comparison of different token selection methods.

#Tokens	Methods	SR % ↑	FLOPs ↓	Time(ms) ↓
0	Baseline	84.4	1.888	52.37
	SparseVLM	79.8	1.358	88.08
	FastV	84.6	1.888	53.10
50	Ours	85.4	1.611	33.43
	SparseVLM	74.6	1.097	61.01
	FastV	83.4	1.888	45.72
100	Ours	83.8	1.295	31.29
	SparseVLM	44.4	0.735	57.42
	FastV	72.8	1.888	45.19
200	Ours	68.3	0.823	30.29

Table 5. LIBERO-Spatial benchmark comparing different methods based on pruning or reuse tokens. Best values in each column are highlighted in **bold**.

signed for long-sequence VLM tasks, where efficiency gains are more pronounced, but struggle in VLA settings, where action sequences are typically short. In contrast, VLA-Cache leverages inter-frame token reuse with negligible overhead, making it effective for robotic action generation.

Ablation on Reusing/Pruning Rate. Table 5 presents a comparative analysis of different methods through an ablation study on the top- k parameter, while also varying the number of pruned or reused tokens. For all methods, increasing the number of reused/pruned tokens leads to a decline in success rates, highlighting the importance of retaining sufficient information for accurate action predictions. Our approach maintains a relatively stable success rate at a reuse rate of 40%, but a more noticeable drop occurs when reusing 200 tokens. In contrast, FastV removes a significant portion of tokens entirely, and its performance drop primarily results from the loss of critical visual details rather than potential errors in token reuse. Additionally, SparseVLM and FastV incur longer inference times due to extra attention operations during GPU execution, whereas VLA-Cache directly updates KV cache entries, making inference more efficient.

Token Selection Strategies As presented in Table 4, we evaluate different token selection strategies for VLA-Cache. The direct reuse of static tokens results in a significant decline in success rate. In contrast, filtering task-relevant tokens maintains a success rate of 82.6%. Notably, our layer-adaptive approach further enhances the success rate to 83.8%, albeit with a marginal increase in computational

overhead from 1.304 FLOPs to 1.382 FLOPs. This overhead arises because fewer tokens are reused in the early layers, which ensures the retention of critical updates in deeper layers, thereby improving overall performance.

Main Results on SIMPLER Table 2 indicates that the VLA-Cache exhibits comparable success rates than the baseline CogACT in the SIMPLER environment while substantially reducing computational overhead. Specifically, VLA-Cache achieves an average success rate of 74.4% in the standard Visual Matching setting compared to 74.8% for CogACT and 62.3% in the Variant Aggregation setting versus 61.3% for CogACT.

The efficiency gains are evident in the FLOPs and inference time measurements. VLA-Cache achieves roughly 20% fewer FLOPs than the baseline, coupled with a 1.37x reduction in inference latency. Notably, these results highlight the portability of VLA-Cache across different action heads, establishing it as a general acceleration strategy for VLA.

5.3. Results on Real Robot

Table 3 illustrates the performance of VLA-Cache in real-world robotic tasks. Among the four tasks, *PickPot* shows a slightly lower success rate than the baseline, whereas VLA-Cache exceeds the baseline on the other three tasks. The method also achieves considerable reductions in FLOPs and inference time. Overall, VLA-Cache improves the average success rate by 2.4%, an outcome that, although unexpected, is potentially explained by a more robust baseline model, which we trained extensively using additional data and more training steps than the LIBERO fine-tuning. With improved robustness as a foundation, VLA-Cache’s ability to prune or reuse redundant tokens may further enhance the model’s resilience, thus yielding higher success rates.

6. Conclusion

In this paper, we introduce **VLA-Cache**, a training-free method for VLA that selectively reuses static tokens while filtering out task-relevant ones, reducing redundant computation without sacrificing accuracy. Additionally, our layer-adaptive token reuse strategy improves model success rates by adjusting token reuse based on attention concentration. Extensive experiments on two VLA models, OpenVLA and CogAct, across two simulation environments, LIBERO and SIMPLER, demonstrate that VLA-Cache achieves a **1.7× speedup** while maintaining performance.

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A. Appendix

A.1. Complexity Analysis Details

Static Token Selection. We compute patch-wise similarity for visual tokens:

$$\text{FLOPs}_{\text{static-sim}} = N_{\text{patch}}^2 D_{\text{patch}} \approx H^2. \quad (16)$$

Since $N_{\text{patch}} = H/p$, this cost remains small relative to Transformer computations.

Task-Relevance Filtering. The attention-based filtering step computes cross-modal importance scores:

$$\text{FLOPs}_{\text{task-filter}} \approx L_t L_v D. \quad (17)$$

A sorting operation of $\mathcal{O}(L \log L)$ follows for threshold selection.

Layer-Adaptive Entropy Computation. The entropy-based reuse strategy involves:

$$\text{FLOPs}_{\text{entropy}} \approx L^2 D. \quad (18)$$

The per-layer reuse ratio is then computed as:

$$\alpha^l = \min\left(k \sum_{j=1}^l R^j, 1\right). \quad (19)$$

These overheads remain modest compared to the full forward pass cost, enabling efficient token reuse.

Final FLOP Reduction. The total FLOP savings across all layers follow:

$$\Delta \text{FLOPs}_{\text{total}} = \sum_{l=1}^{\Omega} \Delta \text{FLOPs}_{\text{layer}}. \quad (20)$$

This confirms that dynamic token reuse significantly reduces computation without sacrificing model performance.

A.2. VLA Cache Inference

Having identified both static tokens and task-relevant tokens as described in Section 4.1, we now detail how these tokens are reused in the VLA decoder via KV caching. Below, we first present a high-level overview of the procedure, then introduce several formulas to clarify the partial update of key-value (KV) representations under our selective token reuse strategy.

Overall Procedure. At time step $t - 1$, while predicting the action for frame I_{t-1} , the model produces the attention weights (used to evaluate task relevance) and the KV cache, $\{\mathbf{K}_{t-1}^l, \mathbf{V}_{t-1}^l\}$ for each layer l . When a new frame I_t arrives, we compare it with I_{t-1} (6) to obtain a set of static tokens sorted by similarity scores, and further filter out any high task-relevance tokens (9). Simultaneously, we determine a layer-specific reuse ratio α^l (12) based on the entropy of attention distributions at time $t - 1$. This yields:

$$\mathcal{P}_{\text{final}} \text{ and } \{\alpha^l\}_{l=1}^{\Omega}, \quad (21)$$

where $\mathcal{P}_{\text{final}}$ denotes the final subset of tokens eligible for reuse, and Ω is the total number of decoder layers.

Selective Token Reuse. During decoding at time t , each decoder layer l reuses only the top- k tokens (determined by α^l and similarity ranking) from $\mathcal{P}_{\text{final}}$. Let $\mathcal{P}_{\text{reuse}} \subseteq \mathcal{P}_{\text{final}}$ be this chosen set of reusable tokens, with positions (IDs) $\{i \mid i \in \mathcal{P}_{\text{reuse}}\}$. For tokens *not* in $\mathcal{P}_{\text{reuse}}$, we recompute their key-value (KV) representations from scratch. Concretely, let $\mathbf{H}_t^l \in \mathbb{R}^{L \times D}$ be the hidden states at layer l for the new frame I_t . The per-layer self-attention requires three components: queries \mathbf{Q}_t^l , keys \mathbf{K}_t^l , and values \mathbf{V}_t^l . We define:

$$\mathbf{Q}_t^l(i) = W_Q^l \mathbf{H}_t^l(i), \quad (22)$$

for all token indices $i \in \{1, \dots, L\}$, where $W_Q^l \in \mathbb{R}^{D \times D}$ is the learnable projection of queries.

For \mathbf{K}_t^l and \mathbf{V}_t^l , we partially reuse cached values from time $t - 1$:

$$\mathbf{K}_t^l(i) = \begin{cases} \mathbf{K}_{t-1}^l(i), & \text{if } i \in \mathcal{P}_{\text{reuse}}, \\ W_K^l \mathbf{H}_t^l(i), & \text{otherwise,} \end{cases} \quad (23)$$

$$\mathbf{V}_t^l(i) = \begin{cases} \mathbf{V}_{t-1}^l(i), & \text{if } i \in \mathcal{P}_{\text{reuse}}, \\ W_V^l \mathbf{H}_t^l(i), & \text{otherwise,} \end{cases} \quad (24)$$

where $W_K^l, W_V^l \in \mathbb{R}^{D \times D}$ are the key and value projection matrices, respectively, and $\mathbf{K}_{t-1}^l(i), \mathbf{V}_{t-1}^l(i)$ are the cached key-value vectors from the previous time step. This partial-update scheme allows us to skip computation for those tokens deemed both static and non-task-critical.

Finally, the self-attention output at layer l is computed as:

$$\text{Attn}(\mathbf{Q}_t^l, \mathbf{K}_t^l, \mathbf{V}_t^l) = \text{Softmax}\left(\frac{\mathbf{Q}_t^l (\mathbf{K}_t^l)^T}{\sqrt{D}}\right) \mathbf{V}_t^l. \quad (25)$$

Only the newly computed tokens update $\mathbf{K}_t^l, \mathbf{V}_t^l$, while reused tokens retain their entries from $\mathbf{K}_{t-1}^l, \mathbf{V}_{t-1}^l$.

Implementation Details. Listing A.2 outlines our partial token reuse within the VLA decoder:

1. **Position IDs and Causal Masks.** We maintain a *cache_position* array reflecting the positions of tokens that require computation. Tokens not recomputed do not receive new position IDs, enabling a pruned causal mask aligned with the updated token set.
2. **Computing Rotary Embeddings.** Once the reusable tokens are omitted from re-encoding, we apply a rotary embedding function to the reduced set of token embeddings to generate position-dependent features for the next layer.
3. **KV Cache Updates.** Only newly computed tokens update their corresponding key-value entries in $\{\mathbf{K}_t^l, \mathbf{V}_t^l\}$. Reused tokens keep their entries from $\{\mathbf{K}_{t-1}^l, \mathbf{V}_{t-1}^l\}$. This partial-update mechanism leverages the permutation-invariance property of Transformers, ensuring consistent attention outputs even if certain tokens are omitted from recomputation.

Since Transformers naturally support skipping previously processed tokens in a self-attention cache, our layer-adaptive token reuse is readily integrated with standard caching strategies. Notably, the most significant reduction in computation occurs when generating the first action token at time t . After that, the autoregressive procedure continues as usual, incurring no additional overhead for subsequent tokens.

Efficiency and Effect on Performance. By leveraging selective token reuse, VLA-Cache decreases the total number of tokens that must be re-encoded and re-attended at each time step t . This leads to a substantial reduction in decoding time, especially given the short sequences in robotic action prediction. Meanwhile, the complexity of predicting subsequent tokens in the same time step follows the usual KV-caching paradigm, adding minimal overhead. In practice, this method preserves task accuracy by *forcing recomputation* of highly dynamic or task-critical tokens while reusing the remainder. We present a detailed evaluation in Section 5, demonstrating that VLA-Cache achieves notable speedups with negligible performance degradation.

A.3. Finetuning Data for Real Robot Experiments

Robot Setup. The setup of the Franka Robot is shown in Figure 6. In this example, a Kinova Jaco robot arm with 6 degrees of freedom is rigidly fixed to the frame. We use a Sony AX53 camera, which is placed opposite the robot arm. The camera is facing the operating table and transmits the video in real time.

Data Collection. Our data collection work is based on the *CLVR_Jaco_Play* dataset. We employed PyBullet as an inverse kinematics (IK) controller. The system receives incremental Cartesian displacement inputs ($\Delta x, \Delta y, \Delta z$) from an Xbox controller, which are processed to generate joint velocity commands. These commands are transmitted to the robotic arm's velocity controller at a 10Hz control frequency for real-time execution. We record four types of observations: Third-person camera observations (**front.cam.ob**), End-effector Cartesian pose (**ee_cartesian_pos.ob**), End-effector Cartesian velocity (**ee_cartesian_vel.ob**), Jaco arm joint positions (**joint_pos.ob**).



Figure 6. Kinova Jaco Robot Setup

Data Preprocessing. The preprocessing procedure was conducted as follows: Initially, the recorded frames underwent center cropping, reducing the resolution from 1280×720 to 912×720 , followed by resizing to 224×224 . Subsequently, episodes were manually selected based on a visual inspection of the video sequences generated from the recorded frames. To minimize potential biases associated with excessively long episodes, those exceeding 250 steps were excluded from the dataset. Furthermore, steps in which all recorded action values were zero were removed to ensure data relevance and integrity.

A.4. Simulated Evaluation Detail.

LIBERO Task Definitions. Similarly, we also utilize all task suites provided in LIBERO for our evaluations. The Robosuite-based robot setup includes the following tasks: 1) “place bowl on plate with spatial variation” (e.g., drawer positions), 2) “pick object” (e.g., ketchup, bowl, apple), 3) “(open / close) target drawer; action object” (e.g., “open top drawer; place apple into drawer”), and 4) “achieve goal using shared objects” (e.g., rearranging spatial relationships or altering object states).

SIMPLER Task Definitions. We utilize all task variants provided in SIMPLER for our evaluations, which include the Google robot setup with the following tasks: 1) “pick Coke can”, 2) “move obj1 near obj2”, 3) “(open / close) (top / middle / bottom) drawer”, and 4) “open top drawer; place apple into top drawer”. Evaluations for the Google robot setup are provided for both Visual Matching (VM) and Variant Aggregations (VA).

Implementation Details. Simulated evaluations for CogACT and SIMPLER are conducted on a single NVIDIA RTX 4090 GPU in BF16 precision. During inference, we use DDIM sampling with 10 steps and a classifier-free guidance (CFG) coefficient of 1.5. Similarly, for OpenVLA and LIBERO, inference is performed on a single NVIDIA RTX 4090 GPU in BF16 precision.

A.5. Additional Simulation Results

Result of Subtask on LIBERO Spatial Task Suit. Table 6 presents detailed results on each subtask in the LIBERO-Spatial suite. We observe that VLA-Cache, along with methods like SparseVLM and FastV, occasionally surpasses the baseline’s success rate on individual subtasks. This suggests that certain redundant tokens may distract the baseline model, and pruning or reusing tokens can in fact enhance its robustness.

Method	Success Rate %↑											FLOPS↓	CUDA Time(ms)↓
	task1	task2	task3	task4	task5	task6	task7	task8	task9	task10	Avg		
Baseline (OpenVLA)	90	90	84	96	70	90	96	76	82	70	84.4	1.888	52.37
SparseVLM	88	60	90	90	60	82	90	92	72	74	79.8	1.367	88.08
FastV	92	90	90	94	58	92	90	80	78	70	83.4	1.888	54.00
VLA-Cache	90	90	88	94	66	84	94	84	76	72	83.8	1.382	32.22

Table 6. Comparison of success rates across different tasks in the LIBERO-Spatial benchmark.

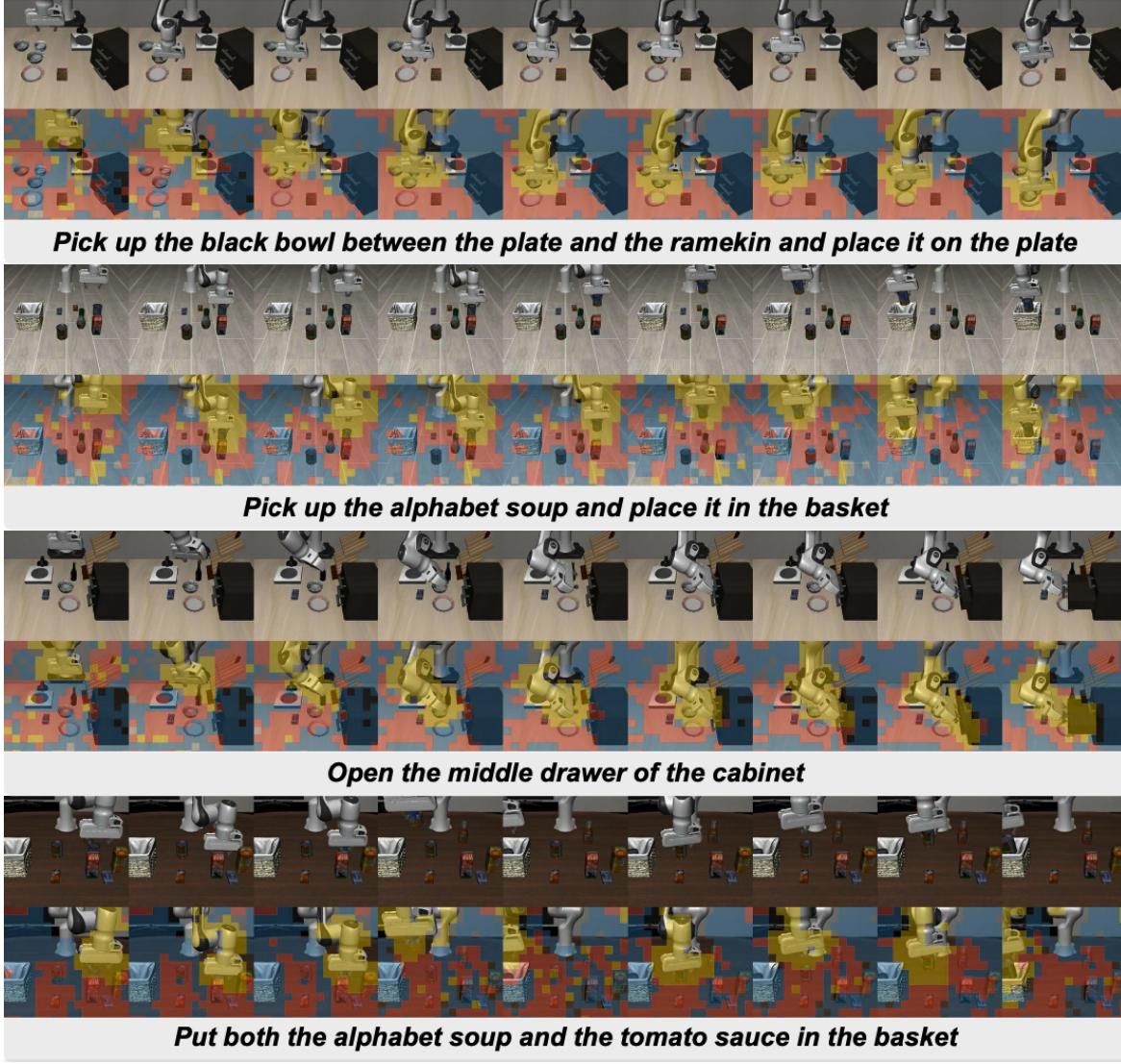


Figure 7. VLA-Cache test results and attention heat map in a simulated environment

Visualization Results. Figure 7 present evaluation examples of each tasks executed by OpenVLA with VLA-Cache in LIBERO.

A.6. Real-World Evaluation Detail.

Task Definitions.

1. **Pick Up Orange Pot** (single-instruction): The robot's goal is to grasp the orange pot and lift it completely off the table. We collected 218 valid demonstrations for the training dataset, with slight random adjustments to the initial positions

of the pot and the robotic arm in each episode. During evaluation, each trial is recorded as a success (1) or failure (0); there is no partial credit.

2. **Place Blue Cube in Box** (single-instruction): The robot's goal is to place the held blue cube into the target container. We collected 212 valid demonstrations for the training dataset, with randomized container positions and robotic arm initial configurations in each episode. During evaluation, each trial is recorded as a success (1) or failure (0); there is no partial credit.
3. **Put Sausage in Blue Pan** (single-instruction): The robot's goal is to stably place the held sausage into the blue pan. We collected 219 valid demonstrations for the training dataset, with randomized pan coordinates and robotic arm joint angles across trials. During evaluation, each trial is recorded as a success (1) or failure (0); there is no partial credit.
4. **Wipe Table** (single-instruction): The robotic arm's goal is to sweep scattered items into a fixed-position dustpan using a broom. For the training dataset, we collected 187 valid demonstrations featuring randomized placements of simulated items (e.g., fries/cheese) on the table and varied initial joint configurations of the robotic arm, while the dustpan location remained fixed. This task explicitly incorporates dynamic environmental variations to rigorously test generalization capabilities. During evaluation, each trial is recorded as a success (1) or failure (0); there is no partial credit.

Visualization Results. Figure 8 present evaluation examples of each tasks executed by OpenVLA with VLA-Cache on the Kinova Jaco Robot Arm.

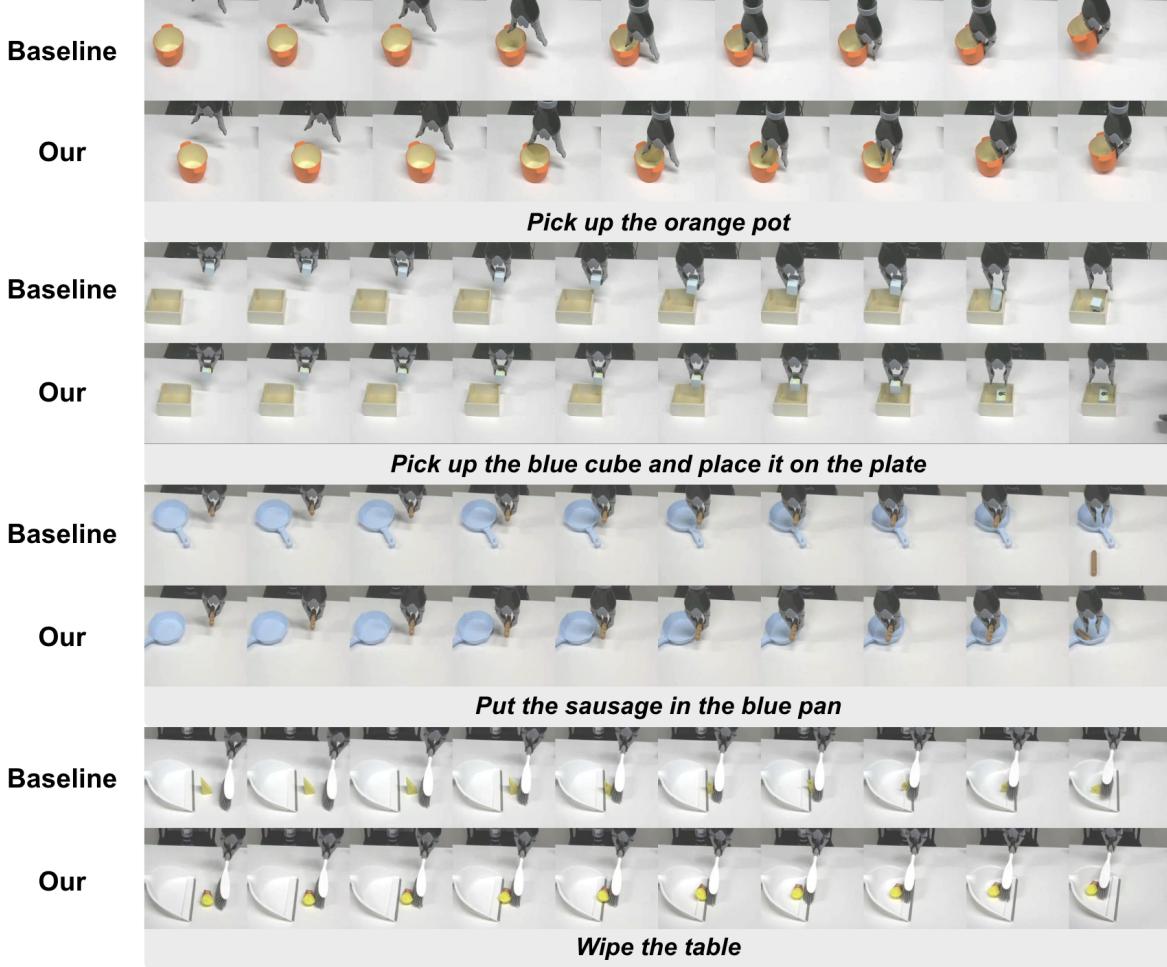


Figure 8. Comparison between baseline(OpenVLA) and VLA-Cache in real environment