MEMORYVLA: PERCEPTUAL-COGNITIVE MEMORY IN VISION-LANGUAGE-ACTION MODELS FOR ROBOTIC MANIPULATION

Hao Shi[1†], **Bin Xie**[2], **Yingfei Liu**[2], **Lin Sun**[4†], **Fengrong Liu**[5†],
Tiancai Wang[2], **Erjin Zhou**[2], **Haoqiang Fan**[2], **Xiangyu Zhang**[3,6], **Gao Huang**[1✉]
[1]Department of Automation, BNRist, Tsinghua University [2]Dexmal
[3]MEGVII Technology [4]Tianjin University [5]Harbin Institute of Technology [6]StepFun
`shi-h23@mails.tsinghua.edu.cn` `gaohuang@tsinghua.edu.cn`
`{xiebin,lyf,wtc,zej,fhq}@dexmal.com`
[†] Work done during interning at Dexmal. [✉] Corresponding author.

ABSTRACT

Temporal context is essential for robotic manipulation because such tasks are inherently non-Markovian, yet mainstream VLA models typically overlook it and struggle with long-horizon, temporally dependent tasks. Cognitive science suggests that humans rely on working memory to buffer short-lived representations for immediate control, while the hippocampal system preserves verbatim episodic details and semantic gist of past experience for long-term memory. Inspired by these mechanisms, we propose MemoryVLA, a Cognition-Memory-Action framework for long-horizon robotic manipulation. A pretrained VLM encodes the observation into perceptual and cognitive tokens that form working memory, while a Perceptual-Cognitive Memory Bank stores low-level details and high-level semantics consolidated from it. Working memory retrieves decision-relevant entries from the bank, adaptively fuses them with current tokens, and updates the bank by merging redundancies. Using these tokens, a memory-conditioned diffusion action expert yields temporally aware action sequences. We evaluate MemoryVLA on 150+ simulation and real-world tasks across three robots. On SimplerEnv-Bridge, Fractal, and LIBERO-5 suites, it achieves 71.9%, 72.7%, and 96.5% success rates, respectively, all outperforming state-of-the-art baselines CogACT and π_0, with a notable +14.6 gain on Bridge. On 12 real-world tasks spanning general skills and long-horizon temporal dependencies, MemoryVLA achieves 84.0% success rate, with long-horizon tasks showing a +26 improvement over state-of-the-art baseline. The project is available at here.

1 INTRODUCTION

Vision-Language-Action (VLA) models (Brohan et al., 2023; Kim et al., 2024; Black et al., 2024; Li et al., 2024a; Kim et al., 2025; Sun et al., 2025), powered by large-scale cross-embodiment robotic datasets (O'Neill et al., 2024; Walke et al., 2023; Brohan et al., 2022; Khazatsky et al., 2024; Bu et al., 2025a) and pretrained Vision-Language Models (VLMs) (Karamcheti et al., 2024; Liu et al., 2023b; Bai et al., 2023a), have achieved remarkable progress in robotic manipulation. However, mainstream VLA models such as OpenVLA (Kim et al., 2024) and π_0 (Black et al., 2024) rely solely on the current observation, thereby overlooking temporal dependencies and performing poorly on long-horizon temporal manipulation tasks. As shown in Fig. 1 (a), *Push Buttons* tasks exhibit almost no visual difference before and after pushing, making it difficult to determine whether the action has already been completed. This highlights the non-Markovian nature of manipulation, where earlier actions influence later decisions, calling for temporal modeling. A naive strategy is to concatenate consecutive frames as input to the VLM. However, it faces two critical limitations: (1) The quadratic complexity of self-attention severely limits the usable temporal context length; (2) Sequential frame inputs are misaligned with the model's single-frame robotic pretraining distribution.

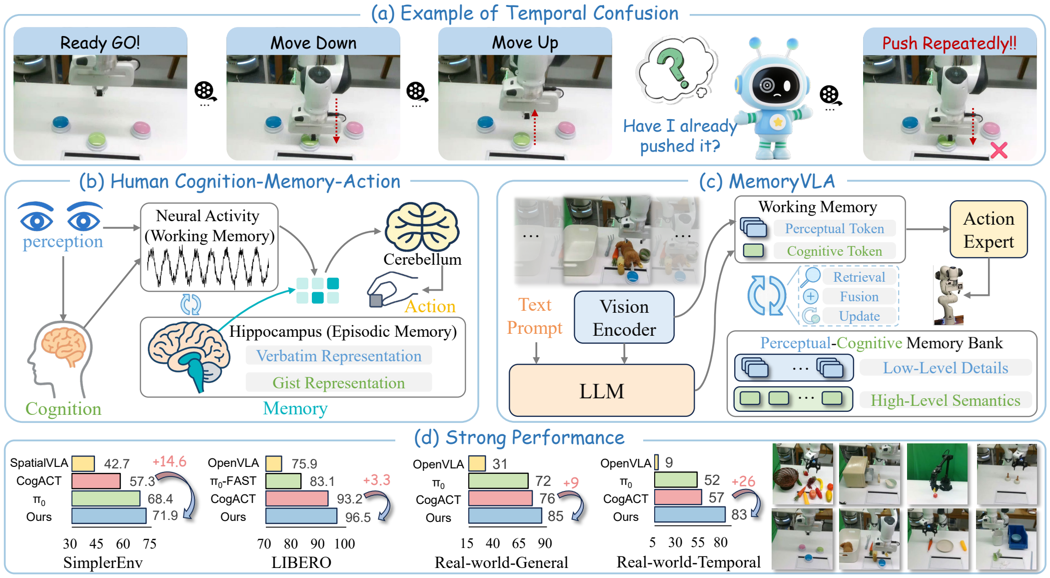


Figure 1: (a) In *Push Buttons* tasks, pre- and post-push states look nearly identical, calling for temporal modeling. (b) Humans handle manipulation tasks via a dual-memory system: working memory (neural activity) supports short-term control, while episodic memory (hippocampus) preserves long-term experience. (c) Inspired by this, MemoryVLA introduces a Perceptual–Cognitive Memory Bank that consolidates low-level perceptual details and high-level cognitive semantics for temporally aware decision making. (d) MemoryVLA outperforms state-of-the-art baselines.

Research in cognitive science (Baddeley & Hitch, 1974; Tulving et al., 1972; Reyna & Brainerd, 1995) demonstrates that humans handle manipulation tasks through a dual-memory system (Fig. 1 (b)). The brain encodes multi-modal sensory inputs into both perceptual and cognitive representations. These representations are buffered in working memory via transient neural activity, providing short-term retention for immediate decision-making. Concurrently, episodic memory, the long-term memory system supported by hippocampus, encodes past experiences with temporal index in two forms: verbatim representations preserving precise details and gist representations capturing abstract semantics. During execution, working memory retrieves decision-relevant contexts from episodic memory and integrates them with current representations to guide actions through cerebellar control, while simultaneously consolidating new experiences into episodic memory.

Drawing on cognitive science insights, we propose **MemoryVLA** (Fig. 1 (c)), a Cognition-Memory-Action framework for robotic manipulation that explicitly models temporal dependencies through a Perceptual–Cognitive Memory Bank (PCMB). First, a vision encoder extracts perceptual tokens from observation, while a large language model (LLM) processes them together with the language instruction, leveraging commonsense priors to produce cognitive tokens. Perceptual and cognitive tokens jointly form the working memory. Second, the PCMB stores both low-level perceptual details and high-level cognitive semantics over long horizons. During retrieval, working memory buffers current tokens and queries the PCMB with temporal positional encodings to fetch decision-relevant historical contexts, which are adaptively fused with current tokens via a gating mechanism while simultaneously updating the PCMB. When capacity is reached, temporally adjacent and semantically similar entries are consolidated to preserve essential information compactly. Finally, a memory-conditioned diffusion action expert is conditioned on cognitive tokens, with perceptual tokens enriching them with fine-grained details, to produce temporally aware robotic action sequences.

We conduct extensive evaluations of MemoryVLA across 3 robots and 150+ tasks with 500+ variations in simulation and real world. For SimplerEnv (Li et al., 2024b), MemoryVLA achieves 71.9% and 72.7% success rates on Bridge and Fractal suites, surpassing CogACT by 14.6 and 4.6 points, further outperforming π_0. For LIBERO (Liu et al., 2023a), it achieves an average success rate of 96.5% across 5 suites (Spatial, Object, Goal, Long, and LIBERO-90), exceeding both CogACT and π_0. For real-world evaluations, we introduce 12 tasks across Franka and WidowX robots, spanning 6 general tasks and 6 long-horizon temporal tasks. MemoryVLA achieves 85% and 83% scores on general and temporal tasks, outperforming CogACT by 9 and 26 points, and substantially surpassing π_0. Moreover, MemoryVLA exhibits strong robustness and generalization under out-of-distribution conditions involving varied backgrounds, distractors, objects, containers, lighting and occlusion.

Our contributions are summarized as follows:

- Inspired by human memory systems from cognitive science, we propose MemoryVLA, a Cognition-Memory-Action framework that leverages VLM commonsense priors, a perceptual-cognitive memory mechanism, and a diffusion action expert to capture long-horizon temporal dependencies for robotic manipulation.
- We design a Perceptual–Cognitive Memory Bank with working memory that enables memory retrieval of decision-relevant contexts across high-level cognition and low-level perception, memory fusion that adaptively integrates them with current representations, and memory consolidation that merges temporally adjacent, semantically similar entries.
- MemoryVLA achieves state-of-the-art performance on SimplerEnv, LIBERO, and real-world. It also demonstrates strong robustness and generalization. On challenging long-horizon real-world tasks, it outperforms CogACT and π_0 by significant margins, underscoring the importance of temporal memory modeling.

2 Related Works

Vision-Language-Action Models Driven by advances in visual foundation models (Radford et al., 2021; Liu et al., 2024a; Zheng et al., 2024a; Zheng et al.; Zhang et al., 2025b), robot imitation learning has progressed rapidly yet remains confined to small, task-specific policies with limited generalization (Shridhar et al., 2023; Zhao et al., 2023; Chi et al., 2023; Goyal et al., 2023). To overcome these, the success of VLMs (Achiam et al., 2023; Touvron et al., 2023; Liu et al., 2023b; Bai et al., 2023b) and large-scale robot datasets (e.g., OXE (O'Neill et al., 2024), Agibot (Bu et al., 2025a)) spawned the vision-language-action (VLA) paradigm. RT-2 (Zitkovich et al., 2023) and OpenVLA (Kim et al., 2024) tokenize continuous actions into discrete tokens and use VLMs for autoregressive prediction as if generating language. In contrast, PI-0 (Black et al., 2024), CogACT (Li et al., 2024a), DexVLA (Wen et al., 2025) and HybridVLA (Liu et al., 2025b) adopt diffusion-based policies (Chi et al., 2023; Liu et al., 2024b) as action heads, leveraging iterative denoising to sample continuous control trajectories that capture diverse multimodal behaviors. However, none of these methods explicitly model temporal dependencies. Robotic manipulation is inherently non-Markovian, and neglecting history leads to failures on long-horizon temporal tasks.

Temporal Modeling in Robotics Temporal modeling has been extensively studied in computer vision and autonomous driving (Wang et al., 2023; Liu et al., 2023c; Feng et al., 2023; Zhou et al., 2024), yet it has not been fully explored in robotic manipulation. Octo (Mees et al., 2024), RoboVLMs (Liu et al., 2025a), and Interleave-VLA (Fan et al., 2025) adapt the VLM paradigm to model robotic video data in an interleaved image-text format. While conceptually elegant, this format is complex to implement and computationally expensive, hindering its widespread application. RoboFlamingo (Li et al., 2023), compresses vision-language representation into a latent token and propagate it via LSTM (Hochreiter & Schmidhuber, 1997). The latent representation is obtained in a relatively coarse manner and the fine-grained perceptual history is largely discarded. TraceVLA (Zheng et al., 2024b) takes a different route, painting historical states as trajectories on the current frame, yet discards rich semantic details. UniVLA (Bu et al., 2025b) incorporates past actions into input prompts, making an initial attempt at temporal modeling. However, it merely serves as a Chain-of-Thought (Wei et al., 2022) process without effectively utilizing historical information. In contrast, we model both high-level cognitive semantics and fine-grained perceptual details within a memory framework, enabling effective temporal modeling for long-horizon manipulation.

3 Method

3.1 Overview of MemoryVLA

Problem Formulation We formulate robotic manipulation in VLA models as a sequential decision-making process, where visual observations and language instructions are mapped to con-

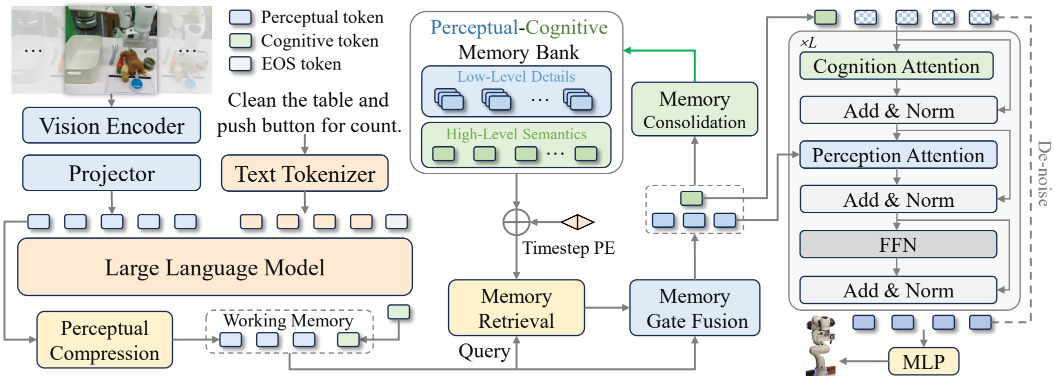


Figure 2: **Overall architecture of MemoryVLA.** RGB observation and language instruction are encoded by a 7B VLM into perceptual and cognitive tokens, forming short-term working memory. The working memory queries a perceptual-cognitive memory bank (PCMB) to retrieve relevant historical context, including high-level semantics and low-level visual details, adaptively fuses it with current tokens, and consolidates the PCMB by merging the most similar neighbors. The memory-augmented tokens then condition a diffusion transformer to predict a sequence of future actions.

trol actions for real world interaction. Given the current RGB image $I \in \mathbb{R}^{H\times W\times 3}$ and a language instruction L, a parameterized policy π outputs a sequence of future actions

$$\mathcal{A} = (a_1, \ldots, a_T) = \pi(I, L), \tag{1}$$

where each action $a_t = [\Delta x, \Delta y, \Delta z, \Delta\theta_x, \Delta\theta_y, \Delta\theta_z, g]^\top$ consists of relative translation, relative rotation (Euler angles), and a binary gripper state $g \in \{0, 1\}$.

Overview MemoryVLA is an end-to-end framework for robotic manipulation, as shown in Fig. 2. The current RGB observation and language instruction are first encoded by a VLM into perceptual and cognitive tokens, forming a working memory, analogous to neural activity in the visual and prefrontal cortex associated with short-term memory. To complement this short-term store, we introduce the Perceptual–Cognitive Memory Bank (PCMB), inspired by the hippocampus, which maintains long-term high-level semantics and fine-grained perceptual details. Working-memory embeddings query the PCMB to retrieve decision-relevant history, adaptively fuse it with current representations via gating, and consolidate the memory by merging temporally adjacent and semantically similar entries when capacity is reached. The resulting representations are then fed into a memory-conditioned diffusion action expert to generate a trunk of N future 7-DoF actions.

3.2 Vision-Language Cognition Module

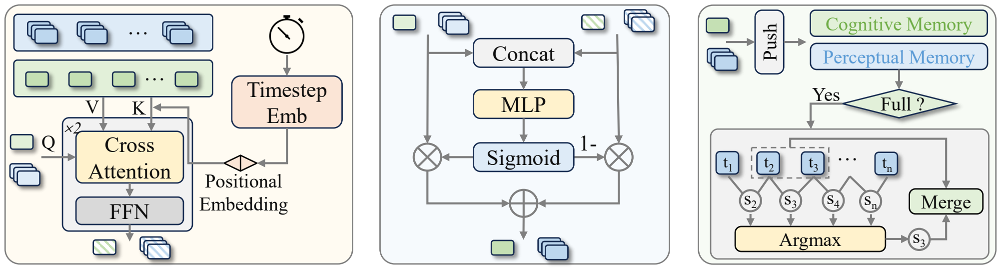
We build upon a 7B–parameter Prismatic VLM (Karamcheti et al., 2024), which is further pretrained on the large-scale cross-embodiment real robot dataset Open-X Embodiment (O'Neill et al., 2024). For visual encoding, we adopt parallel DINOv2 (Oquab et al., 2023) and SigLIP (Zhai et al., 2023) backbones on the current third-person RGB image I, concatenating their features into raw visual tokens. A perceptual compression module, implemented via a SE-bottleneck (Hu et al., 2018), then compresses these tokens into a compact set of perceptual tokens $p \in \mathbb{R}^{N_p\times d_p}$ with $N_p = 256$. In parallel, the raw visual tokens are projected via a linear layer into the language embedding space and concatenated with the tokenized instruction before being fed into the LLaMA-7B (Touvron et al., 2023). The output at the end-of-sentence (EOS) position is taken as the cognitive token $c \in \mathbb{R}^{1\times d_c}$, representing high-level cognitive semantics in compact form. Finally, the perceptual tokens p and cognitive token c are combined to form the short-term working memory for downstream modules.

3.3 Perceptual-Cognitive Memory Module

The Vision–Language Cognition Module yields a working memory

$$M_{\text{wk}} = \{\, p \in \mathbb{R}^{N_p\times d_p},\ c \in \mathbb{R}^{1\times d_c} \},\tag{2}$$

where p and c represent the current perceptual tokens and cognition token, respectively. However, this working memory only reflects the present timestep and lacks temporal dependencies.



(a) Memory Retrieval **(b) Memory Gate Fusion** **(c) Memory Consolidation**

Figure 3: **Details of memory module.** (a) Retrieval: current perceptual and cognitive tokens query the PCMB via cross-attention with timestep positional encoding to fetch relevant historical features. (b) Gate fusion: current and retrieved tokens are adaptively fused via a gate mechanism. (c) Consolidation: the fused tokens are updated into PCMB. When PCMB reaches its capacity, we compute similarities between adjacent entries and merge the most similar pair to maintain compactness.

To address this, inspired by the hippocampus in human memory systems, we introduce the Perceptual–Cognitive Memory Bank (PCMB):

$$M_{\text{pcmb}} = \{\, m^x \mid x \in \{\text{per}, \text{cog}\}\,\}, \tag{3}$$

$$m^x = \{\, m_i^x \in \mathbb{R}^{N_x \times d_x}\,\}_{i=1}^{L}, \quad x \in \{\text{per}, \text{cog}\}, \tag{4}$$

where each perceptual entry m_i^p stores fine-grained visual details and each cognitive entry m_i^c encodes a high-level semantic summary. The bank maintains up to L entries per stream.

Memory Retrieval At each timestep, the working memory M_{wk}, comprising current perceptual tokens $p \in \mathbb{R}^{N_p \times d_p}$ and cognition token $c \in \mathbb{R}^{1 \times d_c}$, acts as a dual query to retrieve historical information required for the current decision from the Perceptual-Cognitive Memory Bank M_{pcmb} as illustrated in Fig. 3 (a). Each memory entry is associated with its episode timestep via a sinusoidal embedding $\text{TE}(\cdot)$, which is added as positional encoding. We then stack all perceptual memories into a tensor $\in \mathbb{R}^{LN_p \times d_p}$ and cognitive memories into a tensor $\in \mathbb{R}^{L \times d_c}$. Scaled dot-product attention between the current tokens and these memory tensors produces raw outputs for both streams:

$$K^x = [\, m_1^x + \text{TE}(t_1);\ \ldots;\ m_L^x + \text{TE}(t_L)\,], \quad V^x = [\, m_1^x;\ \ldots;\ m_L^x\,], \tag{5}$$

$$\hat{H}^x = \text{softmax}\!\left(\frac{q^x (K^x)^\top}{\sqrt{d_x}}\right) V^x, \quad q^x \in \{p,\, c\},\ x \in \{\text{per},\, \text{cog}\}. \tag{6}$$

This attention operation is followed by a feed-forward network to complete one Transformer layer, and applying two such layers yields the final retrieved embeddings H^p and H^c.

Memory Gate Fusion As illustrated in Fig. 3 (b), the gate fusion process integrates the retrieved embeddings H^p and H^c with the current working memory representations through learned gates. For both the perceptual ($x = p$) and cognitive ($x = c$) streams, a gating vector is computed as

$$g^x = \sigma\big(\text{MLP}(\text{concat}[x,\, H^x])\big), \tag{7}$$

and applied to obtain the memory-augmented representation

$$\tilde{x} = g^x \odot H^x + (1 - g^x) \odot x. \tag{8}$$

Here, σ denotes the sigmoid activation and $\odot$ denotes element-wise multiplication. The resulting memory-augmented features $\tilde{p}$ and $\tilde{c}$ are then forwarded to the memory consolidation stage.

Memory Consolidation After gate fusion, the memory-augmented representations $\tilde{p}$ and $\tilde{c}$ are passed to the Memory-conditioned Action Expert and simultaneously updated to the PCMB. When the number of stored entries exceeds L, cosine similarities are computed within each stream (perceptual and cognitive) between adjacent entries. The pair with the highest similarity in each stream is selected and merged by averaging their vectors, thereby reducing redundancy.

$$i_x^* = \arg\max_{i=1,\ldots,L-1} \cos(\tilde{x}_i,\, \tilde{x}_{i+1}), \quad m_{i_x^*}^x \leftarrow \tfrac{1}{2}\big(\tilde{x}_{i_x^*} + \tilde{x}_{i_x^*+1}\big), \quad x \in \{\text{per}, \text{cog}\}. \tag{9}$$

This consolidation mechanism mitigates memory bloat by reducing redundancy, while preserving the most salient perceptual details and semantic abstractions, thereby maintaining a compact representation that supports efficient long-term memory.

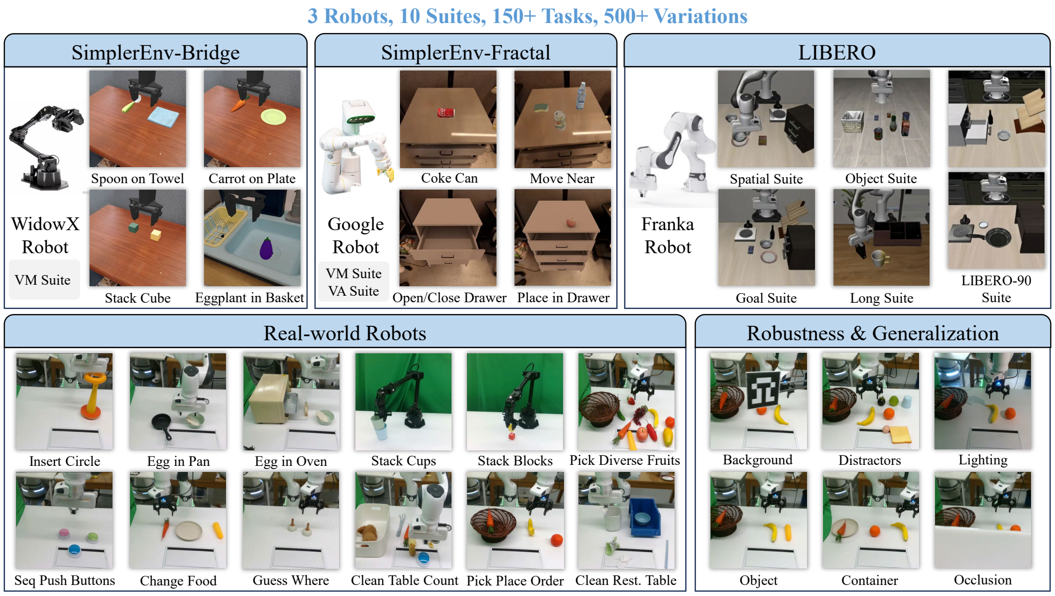


Figure 4: **Experimental setup overview.** Top: three simulation benchmarks, SIMPLER-Bridge with WidowX, SIMPLER-Fractal with Google Robot, and LIBERO with Franka. Bottom: real-world evaluation on two suites, General and Long-horizon Temporal. In total, we evaluate three robots across 10 suites, spanning over 150 tasks and 500 variations.

3.4 Memory-Conditioned Action Expert

Leveraging the memory-augmented working memory $\{\tilde{p}, \tilde{c}\}$, which integrates historical perceptual and cognitive information, the action expert predicts a sequence of future actions $\{a_1, a_2, \ldots, a_T\}$, with $T = 16$. This prediction allows the model to anticipate multi-step trajectories, reduce cumulative error, and provide foresight for long-horizon execution. Since real-world robotic actions lie in a continuous multimodal control space, we adopt a diffusion-based Transformer (DiT) (Peebles & Xie, 2023) implemented with Denoising Diffusion Implicit Models (DDIM) (Song et al., 2020), using 10 denoising steps for efficient yet accurate trajectory generation. This architecture progressively denoises a sequence of noisy action tokens, yielding precise continuous actions.

Specifically, at each denoising step, the noisy action tokens are injected with the sinusoidal encoding of the denoising timestep and concatenated with the cognitive representation $\tilde{c}$. A cognition-attention layer conditions the process with high-level semantic guidance, while a perception-attention layer supplements fine-grained visual details from the perceptual features $\tilde{p}$. The combined representation is then refined through a feed-forward network to obtain the denoised action at that step. The model is trained with mean squared error (MSE) loss between the predicted and target actions, and the final denoised vectors are passed through an MLP to generate continuous 7-DoF robotic actions.

4 Experiments

To comprehensively evaluate MemoryVLA, we organize experiments around five core questions: (1) How does MemoryVLA compare with state-of-the-art methods on SimplerEnv? (Sec. 4.2) (2) How does it perform on LIBERO? (Sec. 4.3) (3) Can it handle both general manipulation and long-horizon temporal tasks on real robots? (Sec. 4.4) (4) What is the impact of each component? (Sec. 4.5) (5) How robust and generalizable is it under diverse environmental conditions? (Appendix A)

4.1 Experimental Setups

Simulation and Real-world Benckmarks. Fig. 4 overviews our evaluation across simulation and real-world, covering 3 robots, 10 suites, 150+ tasks with 500+ variations. SimplerEnv (Li et al., 2024b) includes Bridge suite with a WidowX robot and Fractal suite with a Google robot. Fractal provides two settings: *Visual Matching (VM)* and *Visual Aggregation (VA)*. LIBERO (Liu et al.,

Table 1: **Performance comparison on SimplerEnv-Bridge (Li et al., 2024b) with WidowX robot.** CogACT-Large is our re-evaluated baseline using official weight, and MemoryVLA achieves a +14.6 gain in average success. Entries marked with * are reproduced from open-pi-zero, which leverage additional proprioceptive state inputs; they also adopt Uniform/Beta timestep sampling.

Method	Spoon on Towel	Carrot on Plate	Stack Cube	Eggplant in Basket	Avg. Success
RT-1-X (O'Neill et al., 2024)	0.0	4.2	0.0	0.0	1.1
OpenVLA (Kim et al., 2024)	4.2	0.0	0.0	12.5	4.2
Octo-Base (Team et al., 2024)	15.8	12.5	0.0	41.7	17.5
TraceVLA (Zheng et al., 2024b)	12.5	16.6	16.6	65.0	27.7
RoboVLMs (Liu et al., 2025a)	45.8	20.8	4.2	79.2	37.5
SpatialVLA (Qu et al., 2025)	16.7	25.0	29.2	100.0	42.7
Magma (Yang et al., 2025)	37.5	29.2	20.8	91.7	44.8
CogACT-Base (Li et al., 2024a)	71.7	50.8	15.0	67.5	51.3
π_0-Uniform* (Black et al., 2024)	63.3	58.8	21.3	79.2	55.7
CogACT-Large (Li et al., 2024a)	58.3	45.8	29.2	95.8	57.3
π_0-Beta* (Black et al., 2024)	84.6	55.8	47.9	85.4	68.4
MemoryVLA (Ours)	75.0	75.0	37.5	100.0	**71.9** (+14.6)

Table 2: **Performance comparison on SimplerEnv-Fractal (Li et al., 2024b) with Google robot.** Success rates (%) are reported for *Visual Matching (VM)* and *Visual Aggregation (VA)* suites. MemoryVLA achieves an overall +4.6 gain over CogACT. O./C. denotes Open/Close, and * follow Tab. 1.

Method	Visual Matching (VM)					Visual Aggregation (VA)					Overall
	Coke Can	Move Near	O. / C. Drawer	Put in Drawer	Avg.	Coke Can	Move Near	O. / C. Drawer	Put in Drawer	Avg.	
Octo-Base (Team et al., 2024)	17.0	4.2	22.7	0.0	11.0	0.6	3.1	1.1	0.0	1.2	6.1
RT-1-X (O'Neill et al., 2024)	56.7	31.7	59.7	21.3	42.4	49.0	32.3	29.4	10.1	30.2	36.3
OpenVLA (Kim et al., 2024)	18.0	56.3	63.0	0.0	34.3	60.8	67.7	28.8	0.0	39.3	36.8
RoboVLMs (Liu et al., 2025a)	76.3	79.0	44.9	27.8	57.0	50.7	62.5	10.3	0.0	30.9	44.0
TraceVLA (Zheng et al., 2024b)	45.0	63.8	63.1	11.1	45.8	64.3	60.6	61.6	12.5	49.8	47.8
RT-2-X (O'Neill et al., 2024)	78.7	77.9	25.0	3.7	46.3	82.3	79.2	35.5	20.6	54.4	50.4
Magma (Yang et al., 2025)	75.0	53.0	58.9	8.3	48.8	68.6	78.5	59.0	24.0	57.5	53.2
SpatialVLA (Qu et al., 2025)	79.3	90.0	54.6	0.0	56.0	78.7	83.0	39.2	6.3	51.8	53.9
π_0-Uniform* (Black et al., 2024)	88.0	80.3	56.0	52.2	69.1	–	–	–	–	–	–
π_0-Beta* (Black et al., 2024)	97.9	78.7	62.3	46.6	71.4	–	–	–	–	–	–
CogACT (Li et al., 2024a)	91.3	85.0	71.8	50.9	74.8	89.6	80.8	28.3	46.6	61.3	68.1
MemoryVLA (Ours)	90.7	88.0	84.7	47.2	**77.7**	80.5	78.8	53.2	58.3	**67.7**	**72.7** (+4.6)

2023a) uses a Franka robot and spans five suites (Spatial, Object, Goal, Long, and LIBERO-90). In real world, we evaluate General and Long-horizon Temporal suites on Franka and WidowX robots.

Implementation Details We train on 8 NVIDIA A100 GPUs with PyTorch FSDP, using 32 samples per GPU for a global batch of 256 and a learning rate of 2×10^{-5}. The model takes a single third-person RGB frame at 224×224 together with the language instruction and outputs 7-DoF actions. The LLM is 7B, and the diffusion action expert has $\sim$300M parameters. At inference we use DDIM (Song et al., 2020) with 10 sampling steps and a classifier-free guidance(CFG) (Ho & Salimans, 2022) coefficient of 1.5. Additional details are provided in Appendix B and C.

4.2 Simulated Evaluation on SimplerEnv

Training and Evaluation Setup We evaluate on two SimplerEnv suites: Bridge and Fractal. For SimplerEnv-Bridge, we train on Bridge v2 dataset (Walke et al., 2023) for 50k steps with validation every 2.5k steps. Results are reported at the best validation step, and each task is evaluated with 24 trials to compute success rates. For SimplerEnv-Fractal, we train on the RT-1 dataset (Brohan et al., 2022) for 80k steps with validation every 5k steps. Evaluation covers *Visual Matching (VM)* and *Visual Aggregation (VA)* settings. VM mirrors the real setup to reduce sim-to-real gap, while VA stress-tests robustness by altering background, lighting, distractors, and table textures. The Fractal testbed includes 336 variants, yielding 2,352 trials in total.

Evaluation Results on SimplerEnv-Bridge As shown in Tab. 1, MemoryVLA achieves an average success rate of **71.9%**, a **+14.6** point gain over the CogACT-Large baseline, and surpasses recent

Table 3: **Performance comparison on LIBERO (Liu et al., 2023a) with Franka robot.** Success rates (%) are reported across five suites. * indicates methods using additional proprioceptive and wrist-camera inputs. CogACT results are reproduced by us. For methods without LIBERO-90 results, we report the average over the first four suites.

Method	Spatial	Object	Goal	Long	LIBERO-90	Avg. Success
Diffusion Policy (Chi et al., 2023)	78.3	92.5	68.3	50.5	–	72.4
Octo (Team et al., 2024)	78.9	85.7	84.6	51.1	–	75.1
MDT (Reuss et al., 2024)	78.5	87.5	73.5	64.8	–	76.1
UniACT (Zheng et al., 2025)	77.0	87.0	77.0	70.0	73.0	76.8
MaIL (Jia et al., 2024)	74.3	90.1	81.8	78.6	–	83.5
SpatialVLA (Qu et al., 2025)	88.2	89.9	78.6	55.5	46.2	71.7
TraceVLA (Zheng et al., 2024b)	84.6	85.2	75.1	54.1	–	74.8
OpenVLA (Kim et al., 2024)	84.7	88.4	79.2	53.7	73.5	75.9
CoT-VLA (Zhao et al., 2025)	87.5	91.6	87.6	69.0	–	81.1
π_0-FAST* (Pertsch et al., 2025)	96.4	96.8	88.6	60.2	83.1	85.0
TriVLA (Liu et al., 2025c)	91.2	93.8	89.8	73.2	–	87.0
4D-VLA (Zhang et al., 2025a)	88.9	95.2	90.9	79.1	–	88.6
CogACT (Li et al., 2024a)	97.2	98.0	90.2	88.8	92.1	93.2
π_0* (Black et al., 2024)	96.8	98.8	95.8	85.2	–	94.2
MemoryVLA (Ours)	98.4	98.4	96.4	93.4	95.6	**96.5** (+3.3)

state-of-the-art VLAs including π_0 (Black et al., 2024). Per task, success rates are 75.0% on *Spoon on Towel*, 75.0% on *Carrot on Plate*, 37.5% on *Stack Cube*, and 100.0% on *Eggplant in Basket*.

Evaluation Results on SimplerEnv-Fractal Tab. 2 reports results under *Visual Matching* and *Visual Aggregation* settings. MemoryVLA achieves an overall success rate of **72.7%**, improving CogACT by +4.6 points and surpassing π_0. By setting, the averages are **77.7%** on VM and **67.7%** on VA, gains of +2.9 and +6.4 points over CogACT, respectively. On *Open/Close Drawer* (VM), it reaches 84.7%, a +12.9 point improvement over CogACT; under VA we observe larger gains, including +24.9 on *Open/Close Drawer* and +11.7 on *Put in Drawer*.

4.3 Simulated Evaluation on LIBERO

Training and Evaluation Setup We evaluate on the LIBERO (Liu et al., 2023a) benchmark with a Franka robot across five suites: Spatial, Object, Goal, Long, and LIBERO-90. The first four suites contain 10 tasks each, and LIBERO-90 contains 90 tasks. Following OpenVLA (Kim et al., 2024), 50 demonstrations per task are used. Separate models are trained for Spatial, Object, and Goal for 20k steps each, while Long and LIBERO-90 are trained jointly for 40k steps. Validation is performed every 1k steps and results are reported at the best validation step. Each task is evaluated with 50 trials and per-suite average success rates are reported.

Evaluation Results on LIBERO As shown in Tab. 3, MemoryVLA achieves an overall success rate of **96.5%**, improving CogACT by +3.3 points and surpassing π_0. Per-suite success rates are 98.4% on Spatial, 98.4% on Object, 96.4% on Goal, 93.4% on Long, and 95.6% on LIBERO-90. Note that MemoryVLA uses only third-person RGB, without wrist views or proprioceptive states.

4.4 Real-world Evaluation

Training and Evaluation Setup We evaluate two real-robot suites, *General* and *Long-horizon Temporal*, on Franka and WidowX robots. Both use an Intel RealSense D435i RGB camera mounted in a fixed front view. Images are captured at 640×480 and downsampled to 224×224. The system is integrated via ROS. For *General*, each task uses 50-150 demonstrations and is evaluated from randomized initial states. *Pick Diverse Fruits* comprises five variants with 5 trials per variant (25 total); all other General tasks use 15 trials. For *Long-horizon Temporal*, each task uses 200-300 demonstrations and is evaluated with 10-15 trials using step-wise scoring to reflect progress over sub-goals. Training runs for approximately 5k–20k steps depending on the task and data size.

Evaluation Results on Real-world As shown in Tab. 4, MemoryVLA achieves average success scores of **85%** on the six General tasks and **83%** on the six Long-horizon Temporal tasks, exceeding CogACT by **+9** and **+26** percentage points, respectively, and surpassing π_0 across both suites. On

Table 4: **Performance comparison on real-world experiments with Franka and WidowX robots.** Success scores (%) are reported over six general tasks and six long-horizon temporal tasks. All methods are evaluated with only third-person RGB observation and language instruction.

Method	General Tasks						
	Insert Circle	Egg in Pan	Egg in Oven	Stack Cups	Stack Blocks	Pick Diverse Fruits	Avg. Success
OpenVLA (Kim et al., 2024)	47	27	53	40	13	4	31
π_0 (Black et al., 2024)	67	73	73	87	53	80	72
CogACT (Li et al., 2024a)	80	67	60	93	80	76	76
MemoryVLA (Ours)	87	80	80	93	87	84	**85** (+9)

Method	Long-horizon Temporal Tasks						
	Seq. Push Buttons	Change Food	Guess Where	Clean Table & Count	Pick Place Order	Clean Rest. Table	Avg. Success
OpenVLA (Kim et al., 2024)	6	3	0	15	27	0	9
π_0 (Black et al., 2024)	25	42	24	61	82	80	52
CogACT (Li et al., 2024a)	15	47	40	67	90	84	57
MemoryVLA (Ours)	58	85	72	84	100	96	**83** (+26)

Table 5: **Ablation on memory type and length.** We report average success rates (%) on SimplerEnv-Bridge tasks.

	Variant	Avg. Success
Memory Type	Cognitive Mem.	63.5
	Perceptual Mem.	64.6
	Both	**71.9**
Memory Length	4	67.7
	16	**71.9**
	64	67.7

Table 6: **Ablation on memory retrieval, fusion, consolidation.** We report average success rates (%) on SimplerEnv-Bridge tasks.

	Variant	Avg. Success
Retrieval	w/o Timestep PE	69.8
	w/ Timestep PE	**71.9**
Fusion	Add	67.7
	Gate	**71.9**
Consolidation	FIFO	66.7
	Token Merge	**71.9**

General tasks, we match or exceed the strongest baseline on every tasks, with notable gains on *Egg in Pan* (+13) and *Egg in Oven* (+20). On Long-horizon Temporal tasks, improvements are larger, including +43 on *Seq. Push Buttons*, +38 on *Change Food*, +32 on *Guess Where*, and +17 on *Clean Table & Count*. These results indicate strong real-world competence on general manipulation and highlight the benefits of temporal memory for long-horizon control.

4.5 Ablation Studies

We ablate memory design on SimplerEnv-Bridge to quantify each choice. As shown in Tab. 5, combining perceptual and cognitive memory attains 71.9%, compared with 63.5% for cognitive-only and 64.6% for perceptual-only. A memory length of 16 performs best at 71.9%, whereas 4 and 64 drop to 67.7%. Tab. 6 evaluates retrieval, fusion, and consolidation. Adding timestep positional encoding increases performance from 69.8% to 71.9%. Gate fusion reaches 71.9%, compared with 67.7% for simple addition. Token-merge consolidation achieves 71.9% versus 66.7% with FIFO.

5 Conclusion

Inspired by cognitive science, we propose MemoryVLA, a Cognition-Memory-Action framework for robotic manipulation. It uses a hippocampus-like Perceptual–Cognitive Memory Bank that cooperates with working memory to capture temporal dependencies. VLM commonsense priors further support high-level cognition, while a memory-conditioned diffusion action expert generates temporally aware actions. Across 150+ tasks with 500+ variations on 3 robots spanning SimplerEnv, LIBERO, and real-world, MemoryVLA consistently surpasses CogACT and π_0, achieves state-of-the-art performance, with notable gains on challenging long-horizon temporal tasks. It also demonstrates strong robustness and generalization under diverse OOD conditions. Future directions include (i) developing *memory reflection*, aligning long-term memory to the LLM input space to enable embedding-space chain-of-thought reasoning; and (ii) building *lifelong memory* through biologically inspired consolidation that distills frequently reused experiences into permanent representations, thereby supporting scalable generalization across scenes, tasks, and embodiments.

REFERENCES

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Alan D Baddeley and Graham James Hitch. Working memory (vol. 8). *New York: GA Bower (ed), Recent advances in learning and motivation*, 1974.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023a.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023b.

Kevin Black, Noah Brown, Danny Driess, Adnan Esmail, Michael Equi, Chelsea Finn, Niccolo Fusai, Lachy Groom, Karol Hausman, Brian Ichter, et al.

\

pi_0 : $Avision-language-actionflowmodelforgeneralrobotcontrol.$*arXiv preprint arXiv:2410.24164*, 2024.

Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Joseph Dabis, Chelsea Finn, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, Jasmine Hsu, et al. Rt-1: Robotics transformer for real-world control at scale. *arXiv preprint arXiv:2212.06817*, 2022.

Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Xi Chen, Krzysztof Choromanski, Tianli Ding, Danny Driess, Avinava Dubey, Chelsea Finn, et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. *arXiv preprint arXiv:2307.15818*, 2023.

Qingwen Bu, Jisong Cai, Li Chen, Xiuqi Cui, Yan Ding, Siyuan Feng, Shenyuan Gao, Xindong He, Xuan Hu, Xu Huang, et al. Agibot world colosseo: A large-scale manipulation platform for scalable and intelligent embodied systems. *arXiv preprint arXiv:2503.06669*, 2025a.

Qingwen Bu, Yanting Yang, Jisong Cai, Shenyuan Gao, Guanghui Ren, Maoqing Yao, Ping Luo, and Hongyang Li. Univla: Learning to act anywhere with task-centric latent actions. *arXiv preprint arXiv:2505.06111*, 2025b.

Cheng Chi, Zhenjia Xu, Siyuan Feng, Eric Cousineau, Yilun Du, Benjamin Burchfiel, Russ Tedrake, and Shuran Song. Diffusion policy: Visuomotor policy learning via action diffusion. *The International Journal of Robotics Research*, pp. 02783649241273668, 2023.

Cunxin Fan, Xiaosong Jia, Yihang Sun, Yixiao Wang, Jianglan Wei, Ziyang Gong, Xiangyu Zhao, Masayoshi Tomizuka, Xue Yang, Junchi Yan, et al. Interleave-vla: Enhancing robot manipulation with interleaved image-text instructions. *arXiv preprint arXiv:2505.02152*, 2025.

Tingliang Feng, Hao Shi, Xueyang Liu, Wei Feng, Liang Wan, Yanlin Zhou, and Di Lin. Open compound domain adaptation with object style compensation for semantic segmentation. *Advances in Neural Information Processing Systems*, 36:63136–63149, 2023.

Ankit Goyal, Jie Xu, Yijie Guo, Valts Blukis, Yu-Wei Chao, and Dieter Fox. Rvt: Robotic view transformer for 3d object manipulation. In *Conference on Robot Learning*, pp. 694–710. PMLR, 2023.

Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598*, 2022.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141, 2018.

Xiaogang Jia, Qian Wang, Atalay Donat, Bowen Xing, Ge Li, Hongyi Zhou, Onur Celik, Denis Blessing, Rudolf Lioutikov, and Gerhard Neumann. Mail: Improving imitation learning with selective state space models. In *8th Annual Conference on Robot Learning*, 2024.

Siddharth Karamcheti, Suraj Nair, Ashwin Balakrishna, Percy Liang, Thomas Kollar, and Dorsa Sadigh. Prismatic vlms: Investigating the design space of visually-conditioned language models. In *Forty-first International Conference on Machine Learning*, 2024.

Alexander Khazatsky, Karl Pertsch, Suraj Nair, Ashwin Balakrishna, Sudeep Dasari, Siddharth Karamcheti, Soroush Nasiriany, Mohan Kumar Srirama, Lawrence Yunliang Chen, Kirsty Ellis, et al. Droid: A large-scale in-the-wild robot manipulation dataset. *arXiv preprint arXiv:2403.12945*, 2024.

Moo Jin Kim, Karl Pertsch, Siddharth Karamcheti, Ted Xiao, Ashwin Balakrishna, Suraj Nair, Rafael Rafailov, Ethan Foster, Grace Lam, Pannag Sanketi, et al. Openvla: An open-source vision-language-action model. *arXiv preprint arXiv:2406.09246*, 2024.

Moo Jin Kim, Chelsea Finn, and Percy Liang. Fine-tuning vision-language-action models: Optimizing speed and success. *arXiv preprint arXiv:2502.19645*, 2025.

Qixiu Li, Yaobo Liang, Zeyu Wang, Lin Luo, Xi Chen, Mozheng Liao, Fangyun Wei, Yu Deng, Sicheng Xu, Yizhong Zhang, et al. Cogact: A foundational vision-language-action model for synergizing cognition and action in robotic manipulation. *arXiv preprint arXiv:2411.19650*, 2024a.

Xinghang Li, Minghuan Liu, Hanbo Zhang, Cunjun Yu, Jie Xu, Hongtao Wu, Chilam Cheang, Ya Jing, Weinan Zhang, Huaping Liu, et al. Vision-language foundation models as effective robot imitators. *arXiv preprint arXiv:2311.01378*, 2023.

Xuanlin Li, Kyle Hsu, Jiayuan Gu, Karl Pertsch, Oier Mees, Homer Rich Walke, Chuyuan Fu, Ishikaa Lunawat, Isabel Sieh, Sean Kirmani, et al. Evaluating real-world robot manipulation policies in simulation. *arXiv preprint arXiv:2405.05941*, 2024b.

Bo Liu, Yifeng Zhu, Chongkai Gao, Yihao Feng, Qiang Liu, Yuke Zhu, and Peter Stone. Libero: Benchmarking knowledge transfer for lifelong robot learning. *Advances in Neural Information Processing Systems*, 36:44776–44791, 2023a.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *Advances in neural information processing systems*, 36:34892–34916, 2023b.

Huaping Liu, Xinghang Li, Peiyan Li, Minghuan Liu, Dong Wang, Jirong Liu, Bingyi Kang, Xiao Ma, Tao Kong, and Hanbo Zhang. Towards generalist robot policies: What matters in building vision-language-action models. 2025a.

Jiaming Liu, Hao Chen, Pengju An, Zhuoyang Liu, Renrui Zhang, Chenyang Gu, Xiaoqi Li, Ziyu Guo, Sixiang Chen, Mengzhen Liu, et al. Hybridvla: Collaborative diffusion and autoregression in a unified vision-language-action model. *arXiv preprint arXiv:2503.10631*, 2025b.

Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Qing Jiang, Chunyuan Li, Jianwei Yang, Hang Su, et al. Grounding dino: Marrying dino with grounded pre-training for open-set object detection. In *European conference on computer vision*, pp. 38–55. Springer, 2024a.

Songming Liu, Lingxuan Wu, Bangguo Li, Hengkai Tan, Huayu Chen, Zhengyi Wang, Ke Xu, Hang Su, and Jun Zhu. Rdt-1b: a diffusion foundation model for bimanual manipulation. *arXiv preprint arXiv:2410.07864*, 2024b.

Yingfei Liu, Junjie Yan, Fan Jia, Shuailin Li, Aqi Gao, Tiancai Wang, and Xiangyu Zhang. Petrv2: A unified framework for 3d perception from multi-camera images. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 3262–3272, 2023c.

Zhenyang Liu, Yongchong Gu, Sixiao Zheng, Xiangyang Xue, and Yanwei Fu. Trivla: A unified triple-system-based unified vision-language-action model for general robot control. *arXiv preprint arXiv:2507.01424*, 2025c.

Oier Mees, Dibya Ghosh, Karl Pertsch, Kevin Black, Homer Rich Walke, Sudeep Dasari, Joey Hejna, Tobias Kreiman, Charles Xu, Jianlan Luo, et al. Octo: An open-source generalist robot policy. In *First Workshop on Vision-Language Models for Navigation and Manipulation at ICRA 2024*, 2024.

Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193*, 2023.

Abby O'Neill, Abdul Rehman, Abhiram Maddukuri, Abhishek Gupta, Abhishek Padalkar, Abraham Lee, Acorn Pooley, Agrim Gupta, Ajay Mandlekar, Ajinkya Jain, et al. Open x-embodiment: Robotic learning datasets and rt-x models: Open x-embodiment collaboration 0. In *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 6892–6903. IEEE, 2024.

William Peebles and Saining Xie. Scalable diffusion models with transformers. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4195–4205, 2023.

Karl Pertsch, Kyle Stachowicz, Brian Ichter, Danny Driess, Suraj Nair, Quan Vuong, Oier Mees, Chelsea Finn, and Sergey Levine. Fast: Efficient action tokenization for vision-language-action models. *arXiv preprint arXiv:2501.09747*, 2025.

Delin Qu, Haoming Song, Qizhi Chen, Yuanqi Yao, Xinyi Ye, Yan Ding, Zhigang Wang, JiaYuan Gu, Bin Zhao, Dong Wang, et al. Spatialvla: Exploring spatial representations for visual-language-action model. *arXiv preprint arXiv:2501.15830*, 2025.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PmLR, 2021.

Moritz Reuss, Ömer Erdinç Yağmurlu, Fabian Wenzel, and Rudolf Lioutikov. Multimodal diffusion transformer: Learning versatile behavior from multimodal goals. *arXiv preprint arXiv:2407.05996*, 2024.

Valerie F Reyna and Charles J Brainerd. Fuzzy-trace theory: An interim synthesis. *Learning and individual Differences*, 7(1):1–75, 1995.

Mohit Shridhar, Lucas Manuelli, and Dieter Fox. Perceiver-actor: A multi-task transformer for robotic manipulation. In *Conference on Robot Learning*, pp. 785–799. PMLR, 2023.

Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. *arXiv preprint arXiv:2010.02502*, 2020.

Lin Sun, Bin Xie, Yingfei Liu, Hao Shi, Tiancai Wang, and Jiale Cao. Geovla: Empowering 3d representations in vision-language-action models. *arXiv preprint arXiv:2508.09071*, 2025.

Octo Model Team, Dibya Ghosh, Homer Walke, Karl Pertsch, Kevin Black, Oier Mees, Sudeep Dasari, Joey Hejna, Tobias Kreiman, Charles Xu, et al. Octo: An open-source generalist robot policy. *arXiv preprint arXiv:2405.12213*, 2024.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Endel Tulving et al. Episodic and semantic memory. *Organization of memory*, 1(381-403):1, 1972.

Homer Rich Walke, Kevin Black, Tony Z Zhao, Quan Vuong, Chongyi Zheng, Philippe Hansen-Estruch, Andre Wang He, Vivek Myers, Moo Jin Kim, Max Du, et al. Bridgedata v2: A dataset for robot learning at scale. In *Conference on Robot Learning*, pp. 1723–1736. PMLR, 2023.

Shihao Wang, Yingfei Liu, Tiancai Wang, Ying Li, and Xiangyu Zhang. Exploring object-centric temporal modeling for efficient multi-view 3d object detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 3621–3631, 2023.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Junjie Wen, Yichen Zhu, Jinming Li, Zhibin Tang, Chaomin Shen, and Feifei Feng. Dexvla: Vision-language model with plug-in diffusion expert for general robot control. *arXiv preprint arXiv:2502.05855*, 2025.

Jianwei Yang, Reuben Tan, Qianhui Wu, Ruijie Zheng, Baolin Peng, Yongyuan Liang, Yu Gu, Mu Cai, Seonghyeon Ye, Joel Jang, et al. Magma: A foundation model for multimodal ai agents. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 14203–14214, 2025.

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 11975–11986, 2023.

Jiahui Zhang, Yurui Chen, Yueming Xu, Ze Huang, Yanpeng Zhou, Yu-Jie Yuan, Xinyue Cai, Guowei Huang, Xingyue Quan, Hang Xu, et al. 4d-vla: Spatiotemporal vision-language-action pretraining with cross-scene calibration. *arXiv preprint arXiv:2506.22242*, 2025a.

Yani Zhang, Dongming Wu, Hao Shi, Yingfei Liu, Tiancai Wang, Haoqiang Fan, and Xingping Dong. Grounding beyond detection: Enhancing contextual understanding in embodied 3d grounding. *arXiv preprint arXiv:2506.05199*, 2025b.

Qingqing Zhao, Yao Lu, Moo Jin Kim, Zipeng Fu, Zhuoyang Zhang, Yecheng Wu, Zhaoshuo Li, Qianli Ma, Song Han, Chelsea Finn, et al. Cot-vla: Visual chain-of-thought reasoning for vision-language-action models. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 1702–1713, 2025.

Tony Z Zhao, Vikash Kumar, Sergey Levine, and Chelsea Finn. Learning fine-grained bimanual manipulation with low-cost hardware. *arXiv preprint arXiv:2304.13705*, 2023.

Henry Zheng, Hao Shi, Qihang Peng, Yong Xien Chng, Rui Huang, Yepeng Weng, Gao Huang, et al. Densegrounding: Improving dense language-vision semantics for ego-centric 3d visual grounding. In *The Thirteenth International Conference on Learning Representations*.

Henry Zheng, Hao Shi, Yong Xien Chng, Rui Huang, Zanlin Ni, Tianyi Tan, Qihang Peng, Yepeng Weng, Zhongchao Shi, and Gao Huang. Denseg: Alleviating vision-language feature sparsity in multi-view 3d visual grounding. In *Autonomous Grand Challenge CVPR 2024 Workshop*, volume 2, pp. 6, 2024a.

Jinliang Zheng, Jianxiong Li, Dongxiu Liu, Yinan Zheng, Zhihao Wang, Zhonghong Ou, Yu Liu, Jingjing Liu, Ya-Qin Zhang, and Xianyuan Zhan. Universal actions for enhanced embodied foundation models. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 22508–22519, 2025.

Ruijie Zheng, Yongyuan Liang, Shuaiyi Huang, Jianfeng Gao, Hal Daumé III, Andrey Kolobov, Furong Huang, and Jianwei Yang. Tracevla: Visual trace prompting enhances spatial-temporal awareness for generalist robotic policies. *arXiv preprint arXiv:2412.10345*, 2024b.

Junbao Zhou, Ziqi Pang, and Yu-Xiong Wang. Rmem: Restricted memory banks improve video object segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18602–18611, 2024.

Brianna Zitkovich, Tianhe Yu, Sichun Xu, Peng Xu, Ted Xiao, Fei Xia, Jialin Wu, Paul Wohlhart, Stefan Welker, Ayzaan Wahid, et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. In *Conference on Robot Learning*, pp. 2165–2183. PMLR, 2023.

Appendix

A Robustness and Generalization Evaluation

A.1 Real-world Evaluation

We further assess the robustness and generalization of MemoryVLA in real-world environments under diverse out-of-distribution (OOD) variants. Fig. 5 shows two representative tasks, *Pick Place Order* and *Clean Restaurant Table*, evaluated under unseen backgrounds, distractors, novel objects/containers, lighting variations, and occlusions.

For *Pick Place Order*, MemoryVLA attains near-perfect success under the base setting (100%), unseen background (100%), unseen distractors (92%), unseen lighting (96%), unseen container (100%), and occlusion (96%), with a moderate drop on unseen objects (89%). For *Clean Restaurant Table*, the base success rate is 96%, with unseen background (92%), unseen distractors (86%), unseen lighting (94%), unseen object (94%), unseen container (96%), and occlusion (94%).

These results confirm that MemoryVLA maintains consistently high performance across a wide range of real-world OOD conditions, demonstrating strong robustness and generalization.

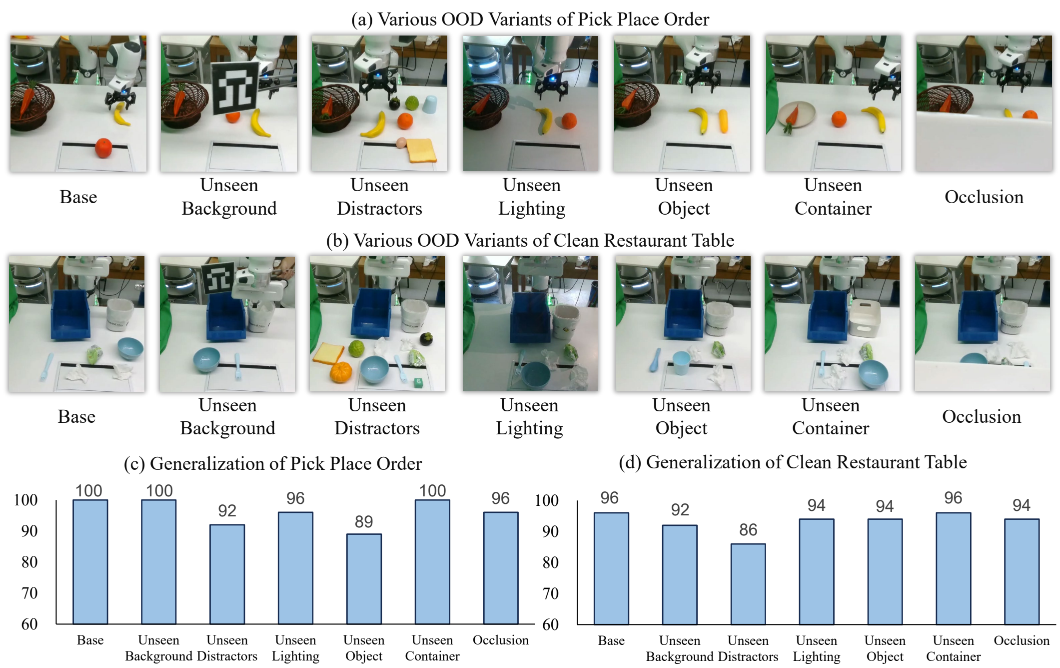


Figure 5: **Robustness and generalization under out-of-distribution (OOD) conditions in real-world.** (a,b) Examples of OOD variants for two representative tasks (*Pick Place Order* and *Clean Restaurant Table*), including unseen backgrounds, distractors, lighting, novel objects/containers, and occlusion. (c,d) Quantitative results showing that MemoryVLA maintains high success rates across these OOD variants, demonstrating strong robustness and generalization in real-world environments.

A.2 Simulation Evaluation

We further conduct robustness and generalization experiments in simulation, considering both pick-and-move tasks and hinge-like object manipulation tasks. Fig. 6 presents results on *Pick Coke Can* and *Move Near*, while Fig. 7 covers *Open/Closed Drawer* and *Place Apple Into Drawer*. These tasks are evaluated under unseen backgrounds, distractors, lighting, textures, and camera views.

For *Pick Coke Can*, MemoryVLA achieves a base success rate of 92.0%, with unseen distractors (90.7%), unseen background (86.7%), unseen lighting (90.7%), and unseen texture (86.7%), while performance drops substantially under unseen camera views (42.0%). For *Move Near*, the base success rate is 76.0%, with unseen distractors (84.0%), unseen background (86.0%), unseen lighting (84.0%), unseen camera view (58.0%), and unseen texture (86.0%). For hinge-like object manipula-

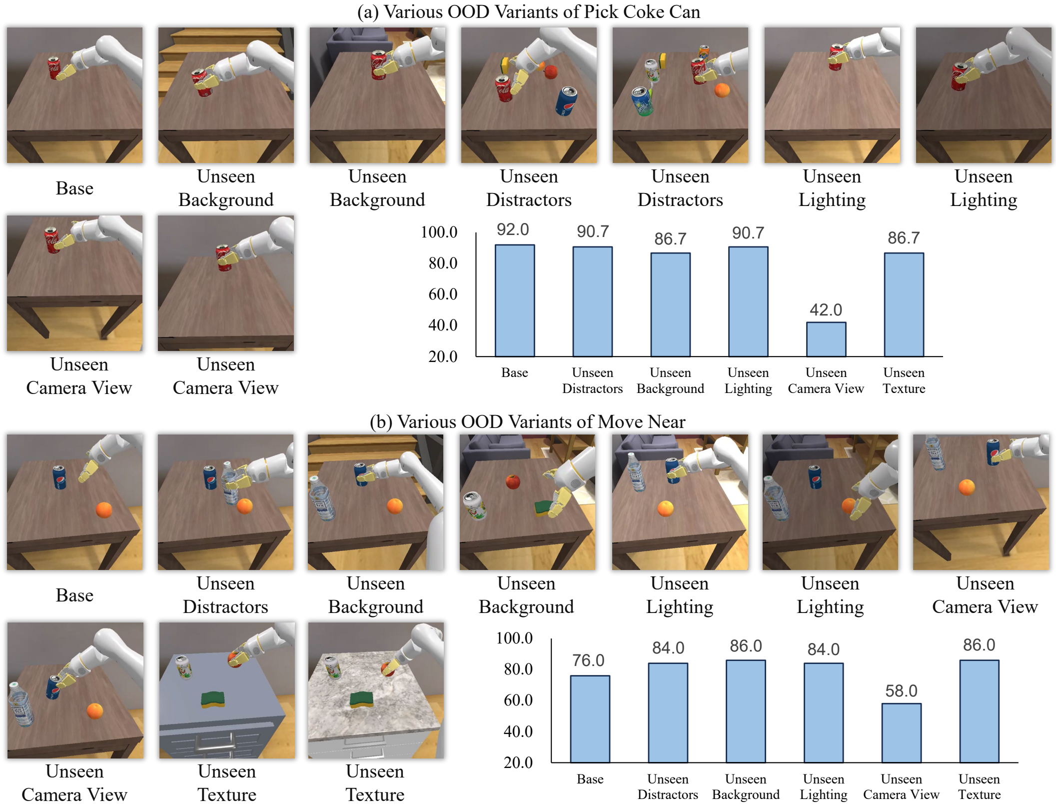


Figure 6: **Robustness and generalization under out-of-distribution (OOD) variants in simulation: Pick and Move tasks.** (a) *Pick Coke Can* and (b) *Move Near* tasks evaluated under unseen backgrounds, distractors, lighting, textures, and camera views. Bar plots report the corresponding success rates, showing that MemoryVLA maintains strong performance across most shifts, with the largest degradation under unseen camera views.

tion, *Open/Closed Drawer* yields a base success rate of 46.3%, unseen background (56.4%), unseen lighting (49.1%), and unseen texture (57.4%). For *Place Apple Into Drawer*, the base success rate is 72.0%, with unseen background (66.0%), unseen lighting (52.0%), and unseen texture (50.0%).

These results show that MemoryVLA generalizes well across moderate distribution shifts such as distractors, backgrounds, and textures, but suffers more under severe changes, especially unseen camera views.

B Additional Training Details

B.1 Hyper-parameters

Table 7: **Training and model hyperparameters.**

Hyperparameter	Value
Batch size	32×8
Learning rate	2×10^{-5}
Repeated diffusion steps	4
Action trunking size	16
Perceptual token channels	256
Max grad. norm	1.0
CFG scale (classifier-free guidance)	1.5

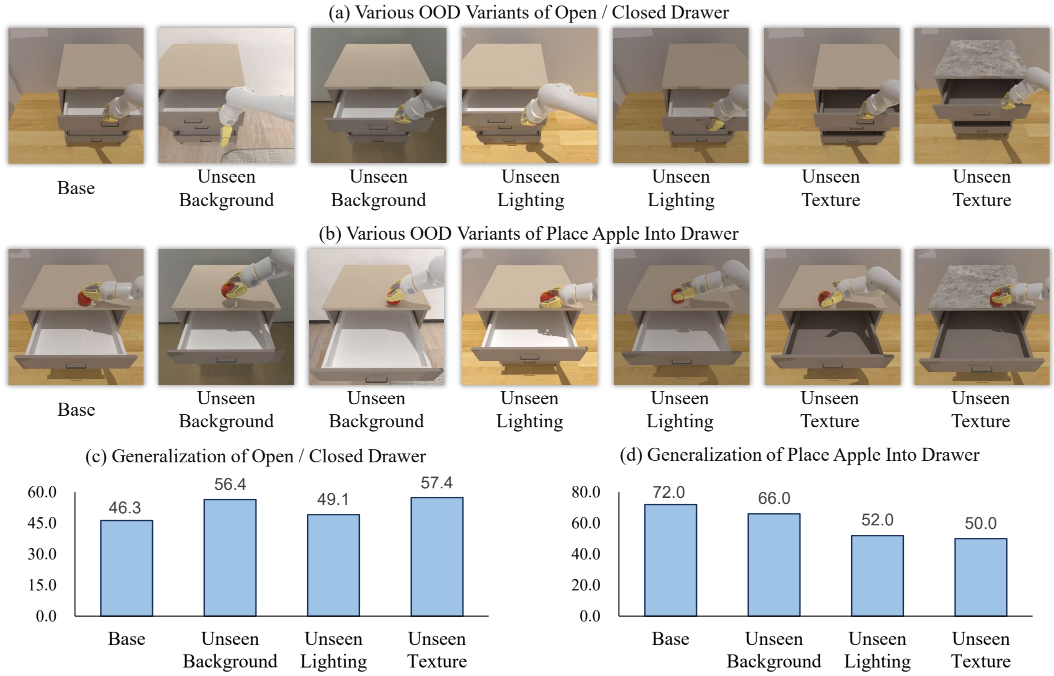


Figure 7: **Robustness and generalization under out-of-distribution (OOD) variants in simulation: Hinge-like object manipulation.** (a) OOD variants of *Open/Closed Drawer* and (b) *Place Apple Into Drawer* tasks, including unseen backgrounds, distractors, lighting, textures, and camera views. Quantitative results indicate that MemoryVLAg̃eneralizes well under moderate shifts, while performance drops notably with camera views changes.

We summarize the main hyperparameters used in our experiments. The global batch size is 256 (32×8 GPUs), the learning rate is 2×10^{-5}, and gradients are clipped at a max norm of 1.0. The policy predicts a 16-step action trunk, and perceptual tokens use 256 channels. The diffusion policy uses 4 repeated diffusion steps during training; inference uses DDIM with 10 sampling steps and a classifier-free guidance scale of 1.5. See Tab. 7 for a concise summary.

B.2 Training Data

Bridge v2 For the SimplerEnv-Bridge benchmark, we train on BridgeData v2 (Walke et al., 2023), a large-scale, language-conditioned real-robot manipulation dataset of roughly 60,000 teleoperated trajectories collected on WidowX robots across diverse tabletop settings. Episodes pair language instructions with demonstrations of skills such as picking, placing, pushing, stacking, and folding.

RT-1 For the SimplerEnv-Fractal benchmark, we use RT-1 (Brohan et al., 2022), a large-scale real-world dataset of roughly 130,000 episodes spanning 700+ tasks, collected over 17 months by the Google Robot fleet and paired with natural-language instructions.

LIBERO LIBERO (Liu et al., 2023a) provides simulation tasks with a Franka robot across five suites: Spatial, Object, Goal, Long, and LIBERO-90, totaling 130 language-conditioned tasks. Each task supplies 50 demonstrations.

Real-world We collect real demonstrations on Franka and WidowX robots using a fixed third-person RGB setup, as shown in Fig. 8 and 9. A front-facing Intel RealSense D435 captures 640×480 RGB at 30 fps.Franka uses a single end-effector per experiment, either the stock parallel gripper or a Robotiq parallel gripper. Demonstrations are gathered by joystick teleoperation. The General suite uses 50-150 demonstrations per task, and the Long-horizon Temporal suite uses 200-300 per task. The system is integrated in ROS.

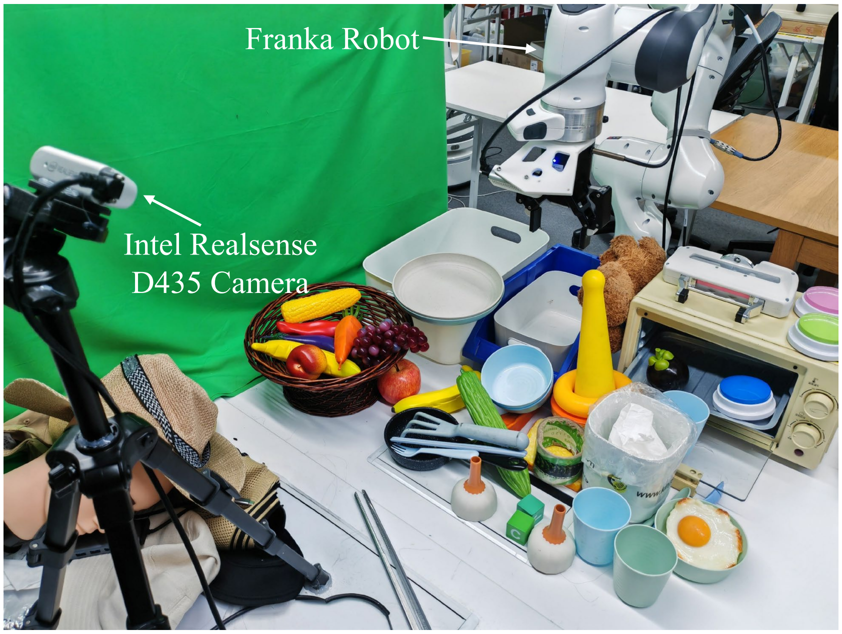


Figure 8: **Franka robot setup.**

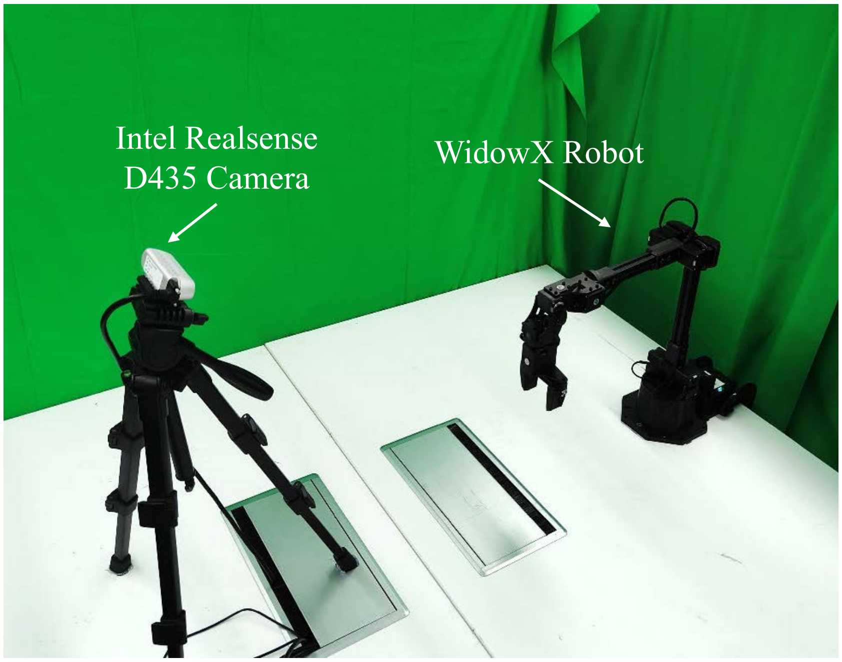


Figure 9: **WidowX robot setup.**

After collection, we perform a standardized preprocessing pipeline. Frames are downsampled to 224×224. We then subsample the video stream by retaining a frame whenever the end-effector translation since the last kept frame exceeds $0.01\,\mathrm{m}$ or the orientation change exceeds $0.4\,\mathrm{rad}$, and we also enforce a maximum gap of 120 frames between kept frames. The processed episodes are converted into the RLDS format for downstream training.

B.3 Training Setup

SimplerEnv-Bridge Models are trained for 50k steps on Bridge v2, the dataloader is implemented as a streaming queue: each episode is pushed as a sequence of frames with an attached episode ID, and batches are constructed by popping consecutive samples. Within a batch, frames come from a single episode whenever possible; if an episode ends before the batch is filled, the remaining slots are completed with frames starting from the next episode. The memory length is fixed to 16.

SimplerEnv-Fractal Models are trained for 80k steps on RT-1. The benchmark defines two protocols: Visual Matching (VM), which mirrors the real-robot setup, and Visual Aggregation (VA), which perturbs background, lighting, distractors, and textures to test robustness. The dataloader design and memory length follow the same setup as in SimplerEnv-Bridge.

LIBERO Following OpenVLA (Kim et al., 2024), we train with 50 demonstrations per task after removing failed trajectories from the dataset. Spatial, Object, and Goal suites are trained separately for 20k steps each, while Long-10 and LIBERO-90 (also referred to as Long-90) are treated as a single family of long-horizon data and trained jointly for 40k steps. The dataloader adopts a grouped sampling strategy: in each iteration, 16 frames are randomly sampled from within a single episode, matching the memory length of 16 used throughout training.

Real-world Models are trained for 5k-20k steps depending on task and dataset size. The General suite contains 50-150 demonstrations per task, while Long-horizon Temporal tasks use 200-300 demonstrations. The dataloader follows the same design as in SimplerEnv-Bridge, but memory length differs by setting: 16 for General tasks and 256 for the longer-horizon Temporal tasks.

B.4 Data Augmentation

We apply standard per-frame augmentations to the third-person RGB stream during training. Augmentations are applied in a fixed order: random resized crop, random brightness, random contrast, random saturation, and random hue. The crop samples 90% of the image area with aspect ratio 1.0 and resizes to 224×224. Brightness is perturbed with magnitude 0.2, contrast and saturation are scaled in $[0.8,\ 1.2]$, and hue is shifted by up to 0.05. All augmentations are disabled at evaluation.

C Additional Evaluation Details

C.1 SimplerEnv

Evaluation follows the official CogACT protocol (Li et al., 2024a). We adopt the same evaluation scripts and use the adaptive action ensemble strategy introduced in CogACT, with ensemble coefficient $\alpha = 0.1$, ensemble horizon set to 7 for Bridge and 2 for Fractal. For Bridge, models are trained for 50k steps and validated every 2.5k steps, since the denoising objective of diffusion models does not reliably indicate policy quality, we report success rates at the best validation step. For Fractal, training runs for 80k steps with validation every 5k steps, and evaluation covers 336 variants in total (Tab. 10), we similarly report success rates at the best validation step, VM and VA settings are evaluated separately.

Since the original paper only reported per-task success rates for CogACT-Base but not for CogACT-Large, we re-evaluated the released CogACT-Large checkpoint in our setup and report those numbers for fairness. For π_0, results are taken from the open-source reproduction open-pi-zero, which provides implementations with both *uniform* and *beta* timestep sampling strategies in flow matching. We report results under float32 precision as in the public release. Note that open-pi-zero does not provide numbers for the Fractal *Visual Aggregation* setting, and thus these are missing.

C.2 LIBERO

Evaluation on LIBERO (Liu et al., 2023a) is conducted across all five suites (Spatial, Object, Goal, Long, and LIBERO-90). Models are validated every 1k steps, and each task is evaluated with 50 trials. Success rates are reported at the best validation step. Unlike SimplerEnv, no action ensemble strategy is used in our LIBERO experiments.

CogACT results are reproduced using the official codebase for fairness. For π_0 and π_0-FAST, we adopt reported numbers, noting that both methods leverage additional wrist-camera views and proprioceptive states, while our approach relies solely on a single third-person RGB. Despite this difference in input modalities, our method consistently surpasses, achieving stronger performance without extra sensory inputs.

C.3 Real-world

Evaluation uses 15-25 trials for General tasks and 10-15 trials for Long-horizon Temporal tasks. For General tasks, *Pick Diverse Fruits* contains five variants (apple, orange, banana, chili, grape), each evaluated with 5 trials (25 total). All other General tasks are evaluated with 15 trials each, and we report task-level success rates.

For Long-horizon Temporal tasks, *Seq. Push Buttons* includes three button orders (blue-pink-green, blue-green-pink, green-blue-pink), each tested with 5 trials. All other tasks are evaluated with 10 trials, and step-wise scoring is adopted to capture partial progress. The scoring rules are as follows:

- **Seq. Push Buttons:** pressing each correct button yields 30, with a bonus of 10 if all three are correct. Loose matching is allowed (slight contact counts as a press).
- **Change Food:** lifting and removing the initial food (30), grasping the new food (30), and placing it on the plate (30), with a 10 bonus for full success.
- **Guess Where:** grasping the cover (30), covering the block (30), and uncovering it (40).
- **Clean Table & Count:** five objects in total. For each object, clearing yields 10 points and pressing the counter yields 10. Small counting errors (incomplete press / one extra press) earn 5; major errors (missed count / multiple extras) earn 0. Empty grasps with clear counting intent incur a 5-point penalty.
- **Pick Place Order:** carrot, banana, and orange must be picked and placed in sequence. Each correct step earns 30, with a 10 bonus for full completion. Any order violation terminates the attempt.
- **Clean Restaurant Table:** five objects in total. Each correctly sorted into trash bin or storage bin scores 20. Misplacement earns 10, and merely lifting without correct placement earns 5.

D Additional Experimental Details

Tab. 8 provides an extended version of Tab. 5 and 6, reporting per-task success rates on SimplerEnv-Bridge for all ablation settings. Gray rows indicate the default configuration.

E Tasks Details

To ensure comprehensive evaluation across simulation and real-world settings, we summarize the task design of each benchmark. We provide task templates, variation types, and the number of variations per task to clarify the diversity and difficulty of evaluation.

E.1 Real-world Tasks

Tab. 9 show the 12 tasks used in real-world evaluation, divided into *General* and *Long-horizon Temporal* suites.

Table 8: **Details of ablation studies.** We report average success rates (%) on SimplerEnv-Bridge when varying five factors: (a) memory type, (b) memory length, (c) memory retrieval, (d) memory fusion, and (e) memory consolidation. Gray rows indicate the default configuration.

Method		Spoon on Towel	Carrot on Plate	Stack Cube	Eggplant in Basket	Avg. Success
(a) Memory Type	Cog. Mem.	70.8	58.3	29.2	95.8	63.5
	Per. Mem.	83.3	54.2	20.8	100.0	64.6
	Both	75.0	75.0	37.5	100.0	**71.9**
(b) Memory Length	4	79.2	75.0	25.0	91.7	67.7
	16	75.0	75.0	37.5	100.0	**71.9**
	64	79.2	54.2	37.5	100.0	67.7
(c) Memory Retrieval	w/o Timestep PE	83.3	62.5	50.0	83.3	69.8
	w/ Timestep PE	75.0	75.0	37.5	100.0	**71.9**
(d) Memory Fusion	Add	75.0	62.5	33.3	100.0	67.7
	Gate	75.0	75.0	37.5	100.0	**71.9**
(e) Memory Update	FIFO	66.7	66.7	33.3	100.0	66.7
	Token Merge	75.0	75.0	37.5	100.0	**71.9**

Table 9: **Real-world tasks details.** We list the instruction template, number of variations, and the corresponding variation types for each task.

Task Name	**Language Instruction Template**	**# Variations**	**Variation Type**
Seq Push Buttons	"Push the {color 1, color 2, and color 3} buttons in sequence"	3	Button color order
Change Food	"Move food off the plate, then put the other food on it"	2	Food object type in plate
Guess Where	"Place a cover over the block, then remove the cover"	1	–
Clean Table & Count	"Clean the table item by item, and push the button after each item cleaned"	1	–
Pick Place Order	"Pick up carrot, banana and orange in order and place them in the basket"	7	Background, distractors, lighting, object, container, occlusion
Clean Restaurant Table	"Place all trash into the trash bin and all tableware into the storage bin"	7	Background, distractors, lighting, object, container, occlusion
Insert Circle	"Insert the circle on the square"	1	–
Egg In Pan	"Put the egg into the pan"	1	–
Egg In Oven	"Put the egg into the oven"	1	–
Stack Cup	"Stack the green cup on the other cup"	1	–
Stack Block	"Stack the yellow block on the red block"	1	–
Pick Diverse Fruit	"Pick up {fruit} and place it in the basket"	5	Fruit category

General Tasks. *Insert Circle*: insert a circle onto a vertical pillar, requiring accurate positioning and insertion. *Egg in Pan*: place an egg into a shallow frying pan, testing grasp stability and gentle placement. *Egg in Oven*: put an egg into a small oven container, involving more constrained placement than the pan. *Stack Cups*: stack one plastic cup on top of another, evaluating vertical alignment and balance. *Stack Blocks*: stack a yellow block on top of a red block, focusing on precise spatial alignment. *Pick Diverse Fruits*: pick a specified fruit from a tabletop with more than ten different fruit types and place it into a basket, testing semantic understanding, visual diversity, and instruction following.

Long-horizon Temporal Tasks. *Seq. Push Buttons*: push three buttons in a specified color sequence, stressing ordered memory and resistance to temporal confusion. *Change Food*: remove a food item from a plate and replace it with another, requiring multi-step sequencing and correct temporal ordering. *Guess Where*: cover a block with a container and later uncover it, testing reversible actions and consistent tracking over time. *Clean Table & Count*: clear items from the table one by one while pressing a counter button after each removal, combining manipulation with explicit progress monitoring. *Pick Place Order*: pick up carrot, banana, and orange in a fixed order

Table 10: **SimplerEnv tasks details.** *VM* = visual-matching, *VA* = variant-aggregation. For *Fractal*, we report *VM* and *VA* separately; all *Bridge* tasks use a single setting.

	Task Name	Language Instruction Template	# Variations	Variation Type
Bridge	Spoon On Tower	"Put the spoon on the tower"	1	–
	Carrot On Plate	"Put the carrot on the plate"	1	–
	Stack Cube	"Stack the green cube on the yellow cube"	1	–
	Eggplant In Basket	"Put the eggplant in the basket"	1	–
Fractal	Pick Coke Can	"Pick up the coke can"	VM: 12 VA: 33	VM: can position×3, URDF×4. VA: base, backgrounds×2, lighting×2, textures×2, camera views×2, distractors×2, can position×3.
	Move Near	"Move the {object} near the {reference}"	VM: 4 VA: 10	VM: URDF×4. VA: base, distractors, backgrounds×2, lighting×2, textures×2, camera views×2.
	Open/Close Drawer	"Open/close the {level} drawer"	VM: 216 VA: 42	VM: env {open/closed}×{top, middle, bottom}; URDF×4; initial pose×9. VA: base, backgrounds×2, lighting×2, cabinet styles×2, env×6.
	Put In Drawer	"Put the {object} into the {level} drawer"	VM: 12 VA: 7	VM: URDF×4; initial pose×3. VA: base, backgrounds×2, lighting×2, cabinet styles×2.

and place them into a basket, enforcing sequence-sensitive planning under temporal dependencies. *Clean Restaurant Table*: sort table items by category, placing trash into a trash bin and tableware into a storage bin, representing a long-horizon task with semantic reasoning and complex multi-stage sequencing.

E.2 SimplerEnv Tasks

Tab. 10 summarizes the tasks in the SimplerEnv benchmark, which consists of two suites: Bridge and Fractal.

The *Bridge* suite contains four tabletop manipulation tasks on WidowX robots: *Spoon on Towel*, *Carrot on Plate*, *Stack Cube*, and *Eggplant in Basket*. Each task is paired with a single language template, focusing on object placement and stacking primitives.

The *Fractal* suite builds on RT-1 data with Google Robots and defines four tasks: *Pick Coke Can*, *Move Near*, *Open/Close Drawer*, and *Put in Drawer*. Each task is evaluated under two protocols. *Visual Matching (VM)* mirrors the real-world setup by varying object positions and URDFs, ensuring alignment between simulation and deployment. *Visual Aggregation (VA)* introduces substantial visual perturbations, including changes in backgrounds, textures, lighting, distractors, and camera views, to stress-test robustness and generalization. Together, VM and VA yield 336 variants, producing 2,352 evaluation trials.

E.3 LIBERO Tasks

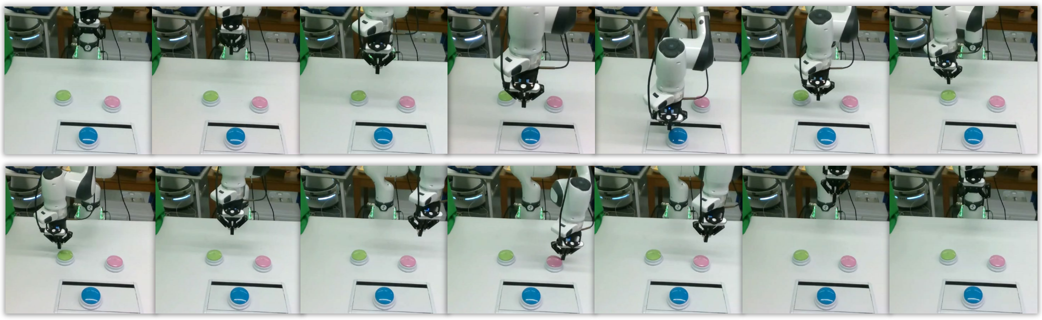
Tab. 11 outlines the five suites of the LIBERO benchmark: Spatial, Object, Goal, Long, and LIBERO-90. LIBERO-Spatial consists of tasks where the same object must be placed across varying target positions. LIBERO-Object focuses on handling diverse objects within a fixed scene layout. LIBERO-Goal contains heterogeneous operations such as opening containers, placing objects, or turning on appliances, performed in an unchanged environment. LIBERO-Long (also called LIBERO-10) introduces ten extended tasks that require multiple sub-goals across different scenes, while LIBERO-90 expands this setting to ninety tasks, providing a substantially more challenging benchmark. In total, LIBERO offers 130 tasks in simulation with a Franka robot.

Table 11: **LIBERO tasks details.** We list the language instruction templates and the total number of tasks per suite.

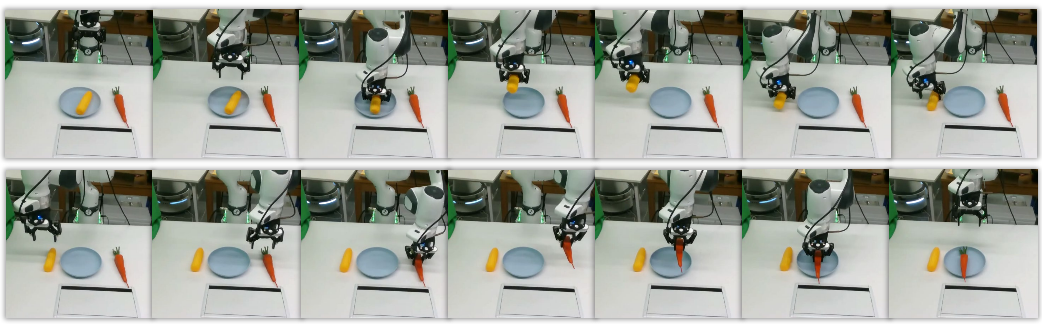
Suite	Language Instruction Templates	#Tasks
Spatial	pick up the *OBJ SPATIAL_REL* and place it on the *TARGET*	10
Object	pick up the *FOOD* and place it in the *CONTAINER*	10
Goal	open/close the *CONTAINER* open the *DRAWER* and put the *OBJ* inside put the *OBJ* on/in the *TARGET* push the *OBJ* to the *POSITION* of the *TARGET* turn on the *APPLIANCE*	10
Long	put both *OBJ1* and *OBJ2* in the *CONTAINER* turn on the *APPLIANCE* and put the *OBJ* on it put the *OBJ* in the *CONTAINER/APPLIANCE* and close it place *OBJ1* on *TARGET1* and *OBJ2* on *TARGET2*/at *REL* of *TARGET2* pick up the *OBJ* and place it in the caddy *COMPARTMENT*	10
90	open/close *CONTAINER/APPLIANCE* [and put *OBJ* on/in it; optionally sequence with another open/close] open *CONTAINER* and put *OBJ* in it put/place *OBJ* in/on/under *TARGET* or at *REL_POS* stack *OBJ1* on *OBJ2* [optionally place them in *CONTAINER*] pick up *OBJ* and put it in *CONTAINER* (basket/tray) place *MUG* on left/right *PLATE* or *BOOK* in caddy/on/under shelf turn on/off *APPLIANCE* [optionally put *OBJ* on it]	90

F QUALITATIVE RESULTS IN REA-WORLD

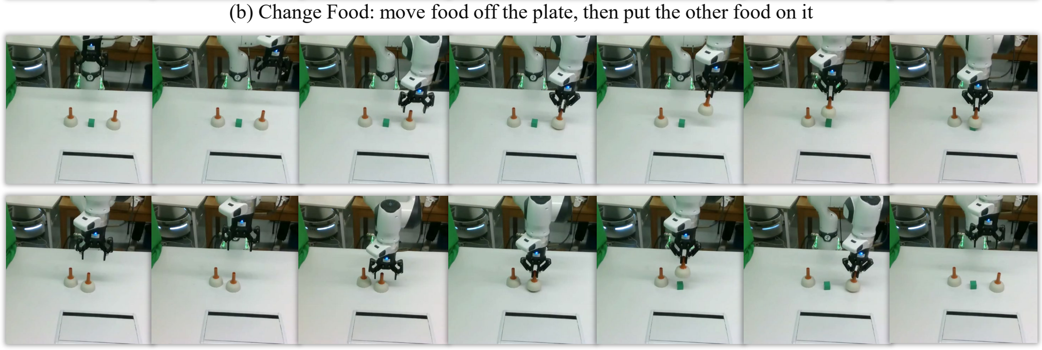
We present qualitative examples to complement the quantitative evaluation. Figs. 10 and 11 illustrate rollouts on long-horizon temporal tasks in real-world. Fig. 12 shows general manipulation tasks in real-world.



(a) Seq Push Buttons: push the blue, green, and pink buttons in sequence

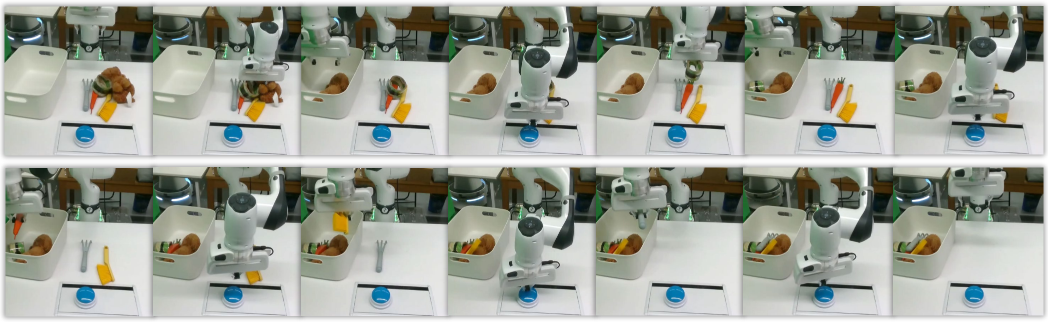


(b) Change Food: move food off the plate, then put the other food on it

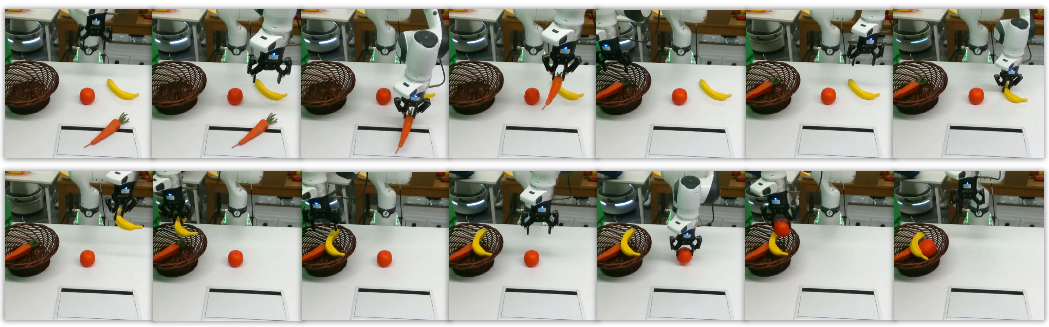


(c) Guess Where: place a cover over the block, then remove the cover

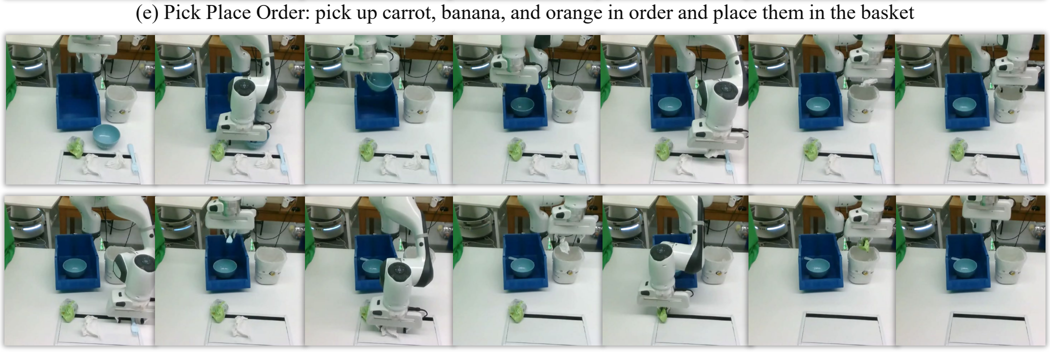
Figure 10: **Qualitative results of MemoryVLA on real-world long-horizon temporal tasks (I).** Representative examples include *Seq Push Buttons*, *Change Food*, and *Guess Where* tasks.



(d) Clean Table & Count: clean the table one by one, and press the button for each item cleaned



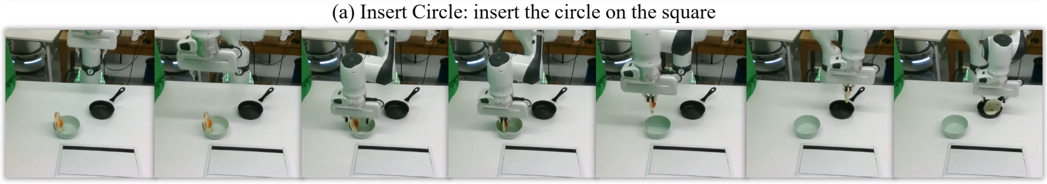
(e) Pick Place Order: pick up carrot, banana, and orange in order and place them in the basket



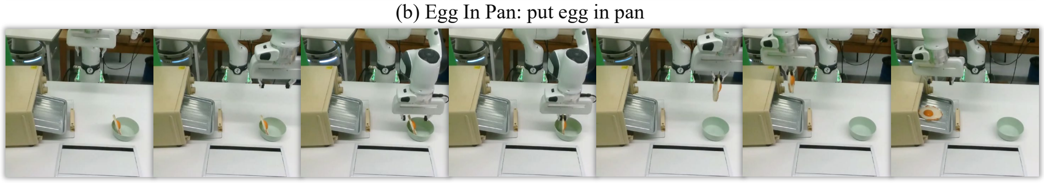
(f) Clean Restaurant Table: place all trash items into the trash bin and all tableware into the storage bin

Figure 11: **Qualitative results of MemoryVLA on real-world long-horizon temporal tasks (II).** Representative examples include *Clean Table & Count*, *Pick Place Order*, and *Clean Restaurant Table* tasks.

(a) Insert Circle: insert the circle on the square



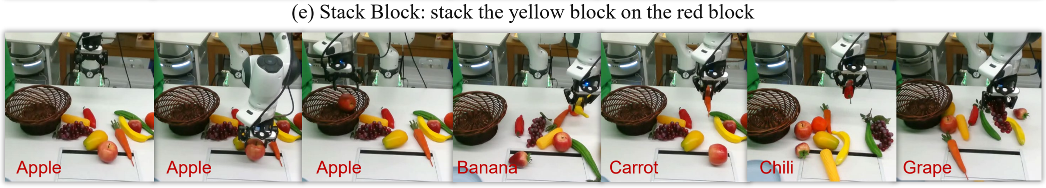
(b) Egg In Pan: put egg in pan



(c) Egg In Oven: put egg in oven

(d) Stack Cup: stack the green cup on the other cup

(e) Stack Block: stack the yellow block on the red block



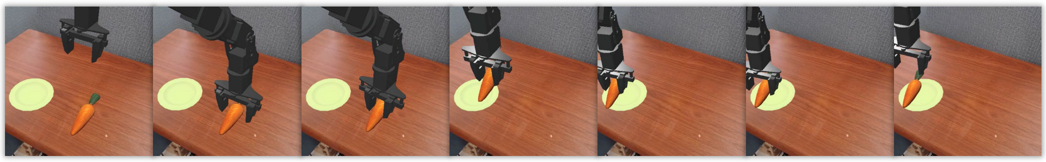
(f) Pick Diverse Fruit: pick up the apple and place it in the basket

Figure 12: **Qualitative results of MemoryVLA on real-world general tasks.** Representative examples include *Insert Circle*, *Egg In Pan*, *Egg In Oven*, *Stack Cup*, *Stack Block*, and *Pick Diverse Fruit* tasks.

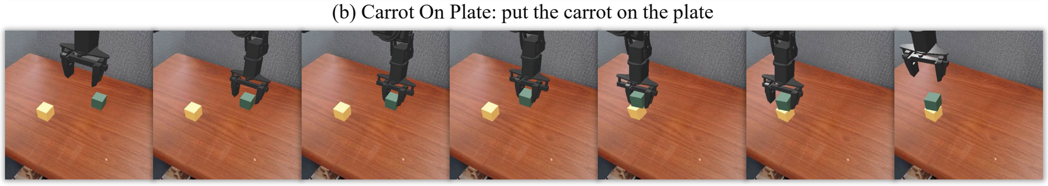
G Qualitative Results in Simulation

Results on simulated environments are visualized in Figs. 13 and 14, covering both Bridge and Fractal suites. Finally, Fig. 15 provides representative trajectories on LIBERO, spanning all five suites.

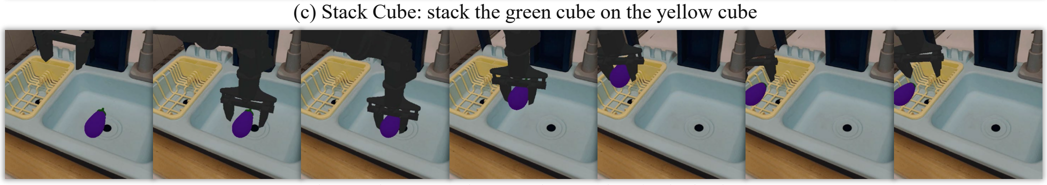
(a) Spoon On Tower: put the spoon on the tower



(b) Carrot On Plate: put the carrot on the plate

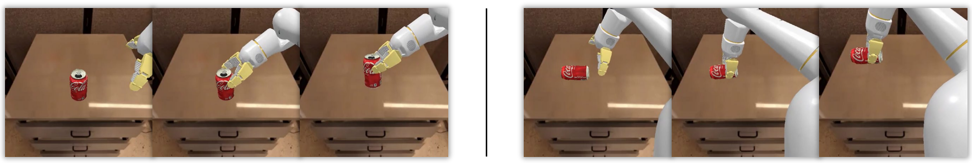


(c) Stack Cube: stack the green cube on the yellow cube

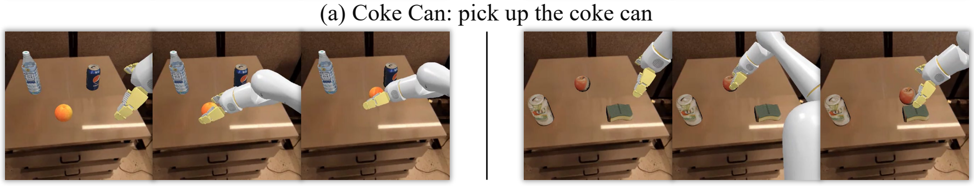


(d) Eggplant In Basket: put the eggplant in the basket

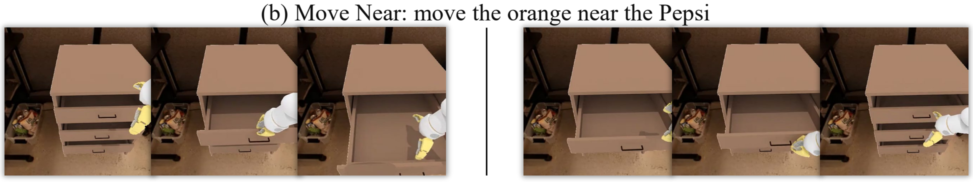
Figure 13: **Qualitative results of MemoryVLA on SimplerEnv-Bridge tasks.** Representative examples include *Spoon On Tower*, *Carrot On Plate*, *Stack Cube*, and *Eggplant In Basket* tasks.



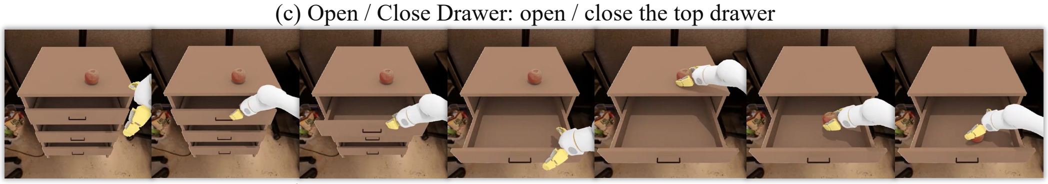
(a) Coke Can: pick up the coke can



(b) Move Near: move the orange near the Pepsi

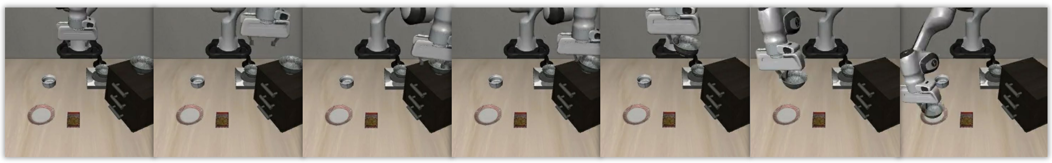


(c) Open / Close Drawer: open / close the top drawer



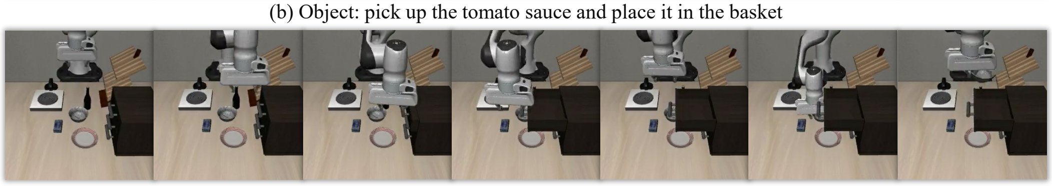
(d)Put In Drawer: put the apple into the top drawer

Figure 14: **Qualitative results of MemoryVLA on SimplerEnv-Fractal tasks.** Representative examples include *Pick Coke Can*, *Move Near*, *Open/Close Drawer*, and *Put In Drawer* tasks.

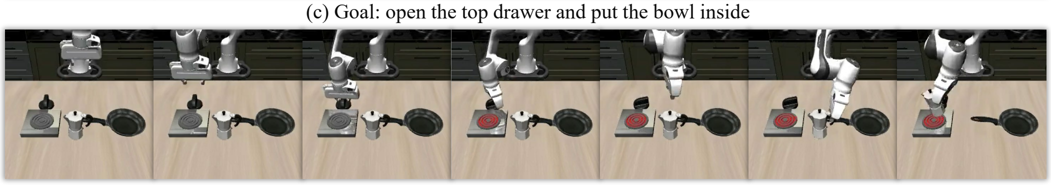


(a) Spatial: pick up the black bowl on the wooden cabinet and place it on the plate

(b) Object: pick up the tomato sauce and place it in the basket



(c) Goal: open the top drawer and put the bowl inside



(d) Long: turn on the stove and put the moka pot on it

(e) LIBERO-90: close the microwave

Figure 15: **Qualitative results of MemoryVLA on LIBERO tasks.** Representative examples include tasks from *Spatial*, *Object*, *Goal*, *Long*, and *LIBERO-90* suites.