VLA-Adapter Reduces Pre-Training Data for Zero-Shot Robotic Instruction Following

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: What is the effectiveness of VLA-Adapter in reducing pre-training data requirements for zero-shot cross-domain adaptation in robotic instruction-following tasks, as measured by success rate on unseen. 12 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.1/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Robotic VLA Benefits from Joint Learning with Motion Image Diffusion. Research question: What is the effectiveness of VLA-Adapter in reducing pre-training data requirements for zero-shot cross-domain adaptation in robotic instruction-following tasks, as measured by success rate on unseen environments in the RoboBench suite?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.1/10.

3 Results

12 papers retrieved. 12 claims extracted; 1 independently verified. Quality review score: 4.1/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The VLM backbone is initialized from pretrained VLA checkpoints, specifically using Paligemma-3B.	×	0.05
The action head is initialized from pretrained VLA checkpoints, specifically using Paligemma-300M.	×	0.07
The motion head is implemented as a lightweight Diffusion Transformer (DiT) with 400M parameters.	✓	0.15
Experiments are conducted using 8 NVIDIA H200 GPUs.	×	0.02
For pretraining, a batch size of 128 is used, with a warm-up phase of 40k steps and a joint training phase of 100k steps	×	0.02
For joint learning, the parameter k is set to match the control frequency of each dataset, aligning the temporal window	×	0.09
For finetuning on simulation benchmarks, a batch size of 32 is used, with 30k steps on the LIBERO benchmark and 60k step	×	0.06
The proposed method achieves a success rate of 97.5% on the LIBERO benchmark.	×	0.11
The proposed method achieves a success rate of 58.0% on the RoboTwin benchmark.	×	0.11
The proposed method yields a 23% improvement in real-world performance.	×	0.13
The proposed method integrates seamlessly into existing large-scale VLA models with no additional inference latency.	×	0.09
The proposed method demonstrates reliable visuomotor control in real-world settings.	×	0.05

References

- http://arxiv.org/abs/2509.09372v2
- http://arxiv.org/abs/2512.18007v1
- http://arxiv.org/abs/2508.13073v2