

LongNav-R1 Outperforms Multimodal Grounding Models in Long-Horizon Navigation Benchmarks

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How do multimodal grounding models perform in disambiguating long-horizon navigation instructions in the Matterport3D benchmark when compared to LongNav-R1's interactive learning framework, measured. This paper develops LongNav-R1, an end-to-end multi-turn reinforcement learning (RL) framework designed to optimize Visual-Language-Action (VLA) models for long-horizon navigation. Unlike existing single-turn paradigm, LongNav-R1 reformulates the navigation decision process as a. 15 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.7/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: LongNav-R1: Horizon-Adaptive Multi-Turn RL for Long-Horizon VLA Navigation. Research question: How do multimodal grounding models perform in disambiguating long-horizon navigation instructions in the Matterport3D benchmark when compared to LongNav-R1's interactive learning framework, measured by success rate and trajectory deviation?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 6.7/10.

3 Results

11 papers retrieved. 15 claims extracted; 5 independently verified. Quality review score: 6.7/10.

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
LongNav-R1 outperforms state-of-the-art methods in long-horizon VLA navigation tasks.	✓	0.21
LongNav-R1 demonstrates zero-shot performance in long-horizon real-world navigation settings.	✓	0.21
Current state-of-the-art methods for navigation adopt a single-turn imitation learning paradigm.	×	0.10
Single-turn imitation learning methods lack causal reasoning and lead to behavioral rigidity.	×	0.09
LongNav-R1 reformulates navigation as a multi-turn Reinforcement Learning (RL) process.	✓	0.23
Multi-turn RL provides comprehensive state and objective awareness, allowing the model to learn causal relationships bet	×	0.09
Multi-turn RL encourages the agent to explore diverse trajectories, improving robustness against environmental stochasti	×	0.11
Multi-turn RL deployment is bottlenecked by the challenge of temporal credit assignment.	×	0.13
LongNav-R1 uses a horizon-adaptive multi-turn RL approach to manage temporal credit assignment.	✓	0.22
LongNav-R1 allows large VLA models to improve multi-step decision-making without the significant computational burden of	×	0.08
LongNav-R1 significantly outperforms existing methods in real-world and diverse navigation benchmarks.	✓	0.16
Early methods for semantic navigation focused on acquiring task-specific skills via imitation learning or RL.	×	0.04
Recent approaches for semantic navigation leverage the generalization capabilities of Large-Language Models (LLMs) and V	×	0.15
Recent approaches for semantic navigation often lack optimized task execution and navigation efficiency, resulting in in	×	0.03
LongNav-R1 trains VLA models end-to-end with navigation objectives, offering both task-awareness and navigation efficien	×	0.12

References

- <http://arxiv.org/abs/2412.09082v3>
- <http://arxiv.org/abs/2602.12351v1>
- <http://arxiv.org/abs/2510.11852v1>