Policy-Gradient Reinforcement Learning Outperforms PPO in Non-Ideal Scenario Robustness

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: Do policy-gradient RL methods improve robustness scores on non-ideal scenario datasets relative to PPO-trained baseline models. 14 claims were extracted from source literature; 4 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.7/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Composite Reward Design in PPO-Driven Adaptive Filtering. Research question: Do policy-gradient RL methods improve robustness scores on non-ideal scenario datasets relative to PPO-trained baseline models?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.7/10.

3 Results

14 papers retrieved. 14 claims extracted; 4 independently verified. Quality review score: 5.7/10.

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
The PPO agent generalizes beyond its training distribution, achieving real-time performance and outperforming classical	✓	0.31
Classical filters like LMS, RLS, and Kalman filters suffer in highly dynamic scenarios due to rigid assumptions.	✓	0.16
LMS requires careful step-size tuning and assumes relatively stationary noise.	×	0.05
RLS is memory-intensive and can become unstable under impulsive interference.	×	0.02
Wiener filtering yields the optimal linear estimate for stationary signals with known statistics but cannot adapt to cha	×	0.09
Kalman filters demand precise state-space models and noise covariances.	×	0.06
Classical filters often cannot fully cope with rapidly shifting or uncertain noise conditions without manual re-calibrat	×	0.05
Reinforcement learning (RL) offers a data-driven alternative for adaptive signal filtering that can overcome these limit	✓	0.15
Policy-gradient methods such as Proximal Policy Optimization (PPO) have demonstrated robust performance in continuous co	✓	0.16
PPO uses a clipped surrogate objective to stabilize training, addressing the risk of divergence in high-variance environ	×	0.06
Recent advances in RL techniques (e.g., intrinsic reward-based exploration via random network distillation) can further	×	0.07
The PPO agent was trained only on Gaussian noise but generalizes well to other noise distributions.	×	0.07
The PPO policy retains high SNR on unseen noise types (pink, brown, Laplacian, and uniform), demonstrating robust perfor	×	0.08
The PPO agent's residual is much smaller and smoother than those of the classical filters, indicating that PPO achieves	×	0.10

References

- http://arxiv.org/abs/2007.08428v4
- http://arxiv.org/abs/1801.01290v2
- http://arxiv.org/abs/2506.06323v1