Continuous Latent Action Models and Discrete Tokens under Sensor Noise in CalAct

Assignee Research

June 9, 2026

Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: How do continuous latent action models and discrete token methods differ in robustness to sensor noise when evaluated on the CalAct benchmark's varying lighting and occlusion conditions. 11 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.7/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Advancing Unsupervised Low-light Image Enhancement: Noise Estimation, Illumination Interpolation, and Self-Regulation. Research question: How do continuous latent action models and discrete token methods differ in robustness to sensor noise when evaluated on the CalAct benchmark's varying lighting and occlusion conditions?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.7/10.

3 Results

4 papers retrieved. 11 claims extracted; 0 independently verified. Quality review score: 3.7/10.

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 framework for low-light imaging can be formulated as x = y $\otimes$s + v, where x denotes the low-light input corrupted by	×	0.11
The unsupervised learning framework consists of a precursor Self-Calibrated Denoiser (SCD) and a subsequent Learnable Il	×	0.10
The learning paradigm can be formulated as SCD -to -LII: \textregistered{}u = x -v, s = u y.	×	0.02
Under low-light conditions, it is easier to accurately estimate noise characteristics.	×	0.12
Brightening the image first can amplify noise intensity, and noise estimation accuracy diminishes under high-brightness	×	0.08
The proposed method achieves an ABE of 0.409, 0.255, and 0.206 for σref. 5, 15, and 25 respectively.	×	0.01
The proposed method achieves an ABE of 0.137 and 0.104 for σref. 35 and σ3 respectively.	×	0.01
The proposed method achieves a PSNR of 35.2346 and 35.6878 for w/ Noise Input and Original respectively.	×	0.04
The proposed method achieves a PSNR of 37.0639 for LOL dataset.	×	0.04
The proposed method achieves a PSNR of 18.1820, 15.2660, and 18.1820 for configurations M1, M2, and M3 respectively.	×	0.01
The proposed method achieves a PSNR of 15.2660 for configuration M4.	×	0.02

References

- http://arxiv.org/abs/2405.19595v1
- http://arxiv.org/abs/2305.10223v4
- http://arxiv.org/abs/1002.1148v1