Generation of Synthetic Low-light Images Using Physics-based Methods Towards Enhancement.

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Overview

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- Motivation
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- Problem Statement and Objectives
- Approach
- Dataset Analysis
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Introduction to Synthetic Image Generation Towards Enhancement

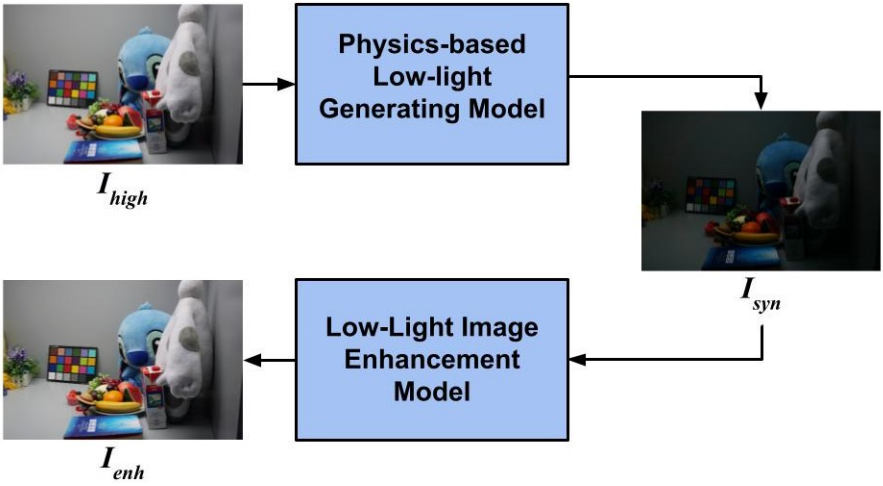
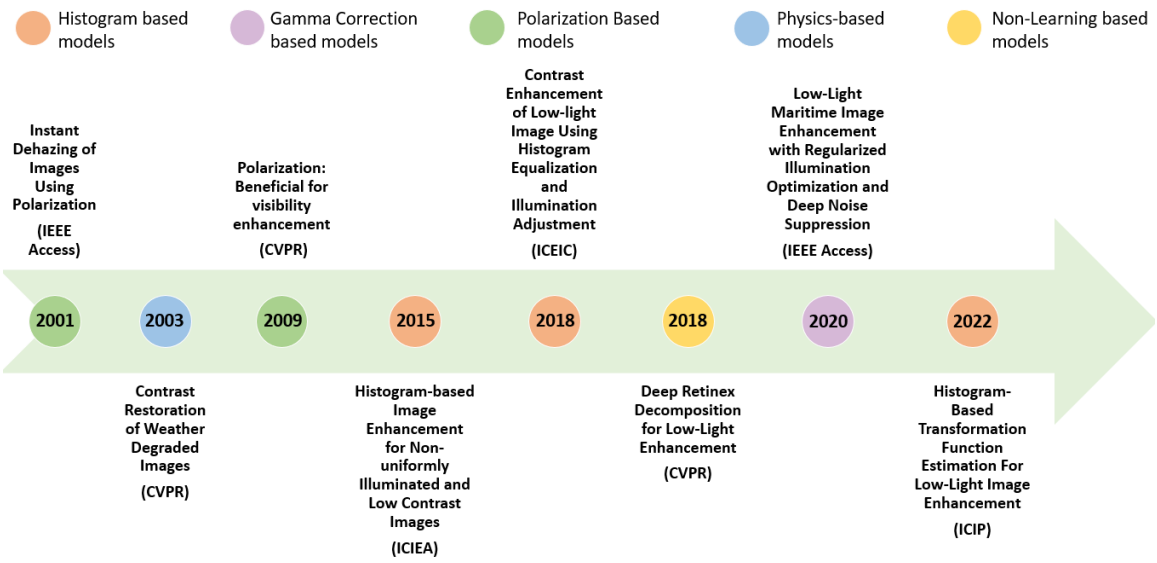


Figure: Overall Framework

Motivation for Synthetic Image Generation Towards Enhancement

- A physics-based model represents the governing laws of nature that innately embeds the concepts of time, space, causality and generalizability.
- This approach ensures that the model not only learns from examples but also possesses the ability to apply its understanding to novel scenarios.
- Once trained on the principles of physics, they can adapt to new situations, making them more robust and capable of handling a variety of real-world challenges.

Literature Towards Generation and Enhancement



Problem Statement and Objectives

Problem Statement

To generate synthetic low-light images using physics principles on retinex theory, towards enhancement

Objectives

- Physics-based generation of low-light images.
- Evaluation of enhancement methods through generated data.
- Performance comparison with state-of-the-art methods on benchmark and generated datasets.

Approach Towards Synthetic Data Generation

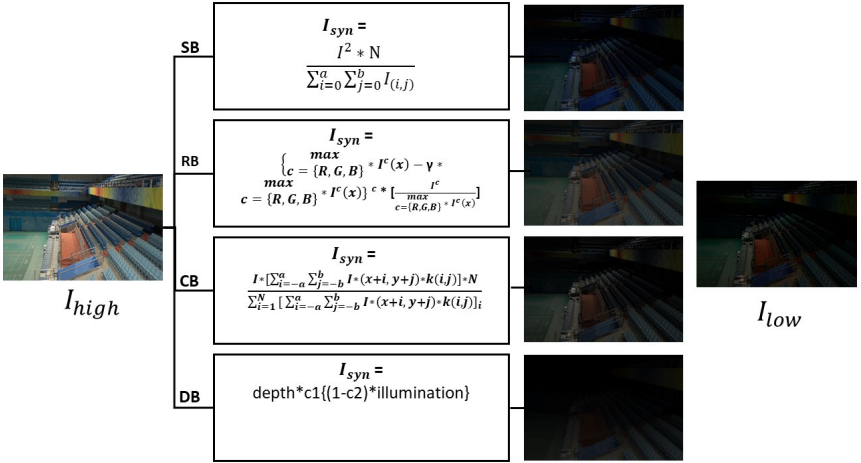


Figure: I_{syn} generation mathematical equations of SB: Statistical-based, RB: Retinex-based, CB: Convolution-based, DB: Depth Estimation-based

Dataset Analysis / Description

LoL Dataset

- Training: 450 pairs
- Testing: 35 pairs

Figure: Dataset images

Experimental Results of Statistical-based Method

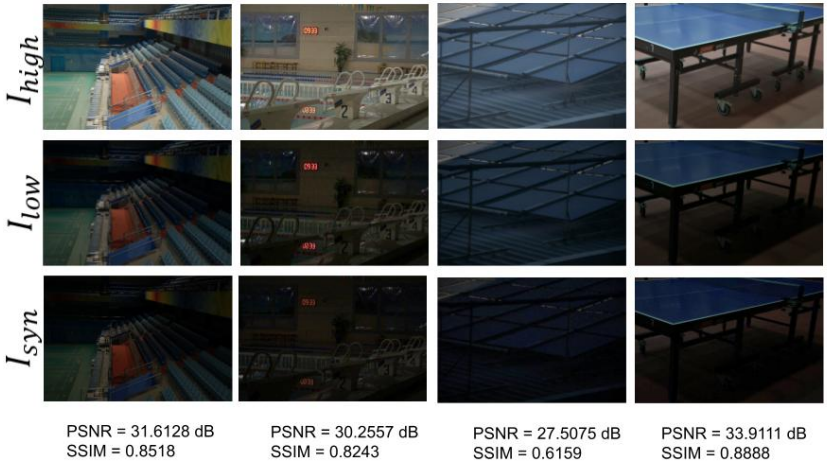


Figure: Results of Statistical-based Method

Experimental Results of Retinex-based Method

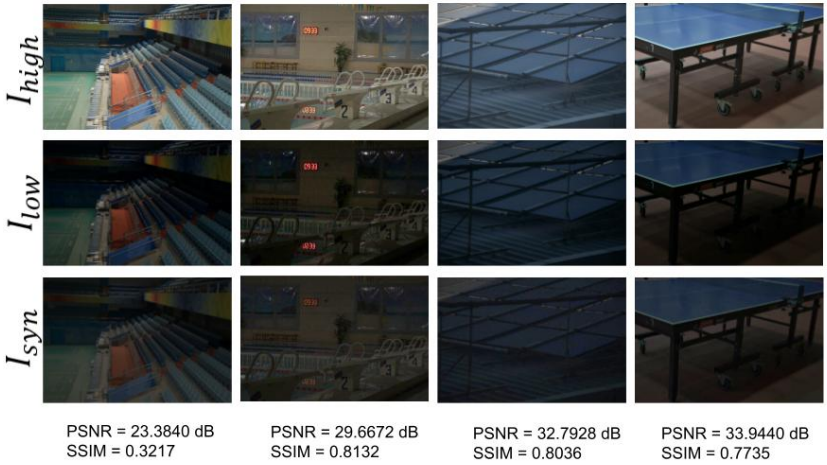


Figure: Results of Retinex-based Method

Experimental Results of Convolution-based Method

Figure: Results of Convolution-based Method

Experimental Results of Depth Estimation-based Method

Figure: Results of Depth Estimation-based Method

Comparison Results of Four Methods

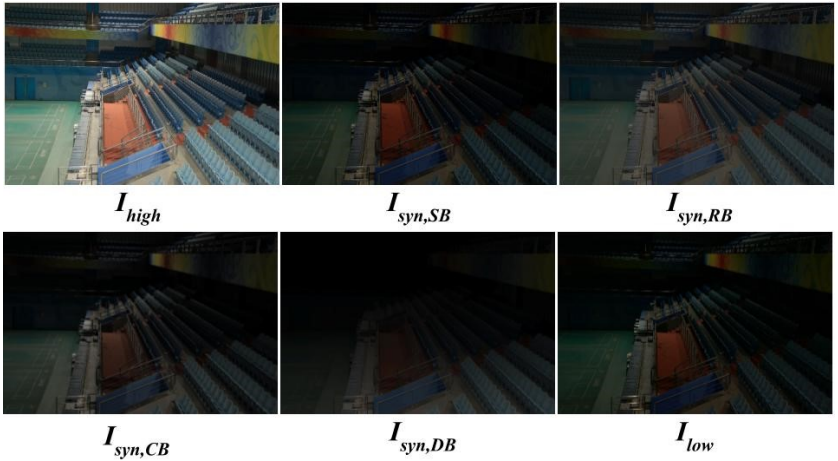


Figure: Comparison of Data Generation of Four Methods

Histogram Comparison Results of Four Methods

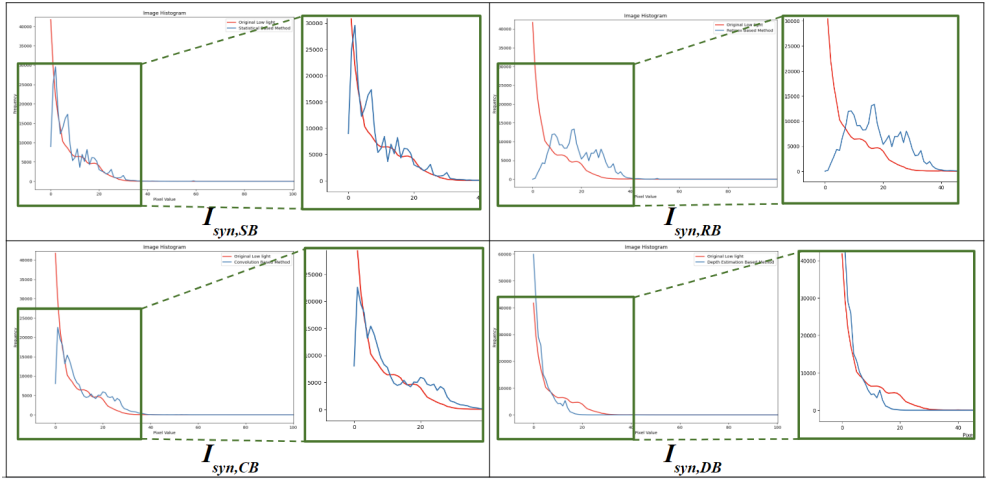


Figure: Histogram Comparison of Four Methods

Histogram Comparison Results of Four Methods

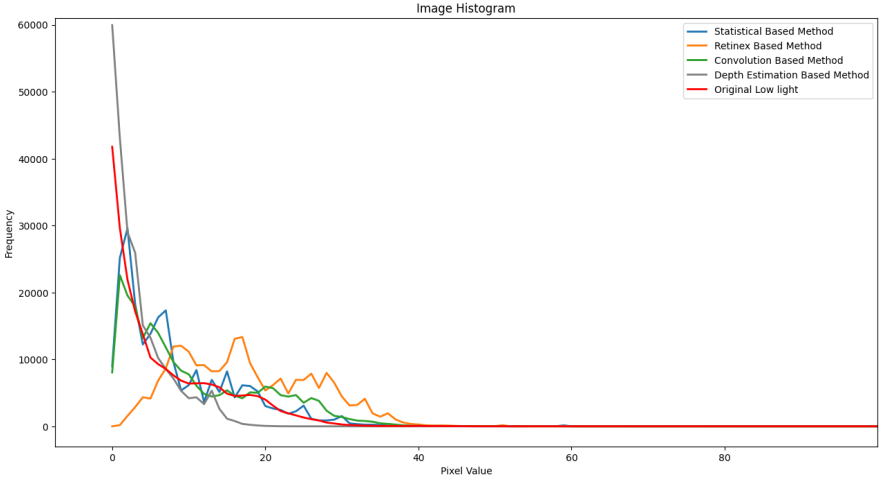


Figure: Histogram Comparison of Four Methods

Kullback-Leibler Divergence Score

Table: KL Divergence Scores Obtained for Four Methods

Methods	**KL Divergence Score**
Statistical-based Method (SB)	0.7439
Retinex-based Method (RB)	1.071
Convolution-based Method (CB)	**0.644**
Depth Estimation-based Method (DB)	1.3773

Experimental Results of Image Enhancement

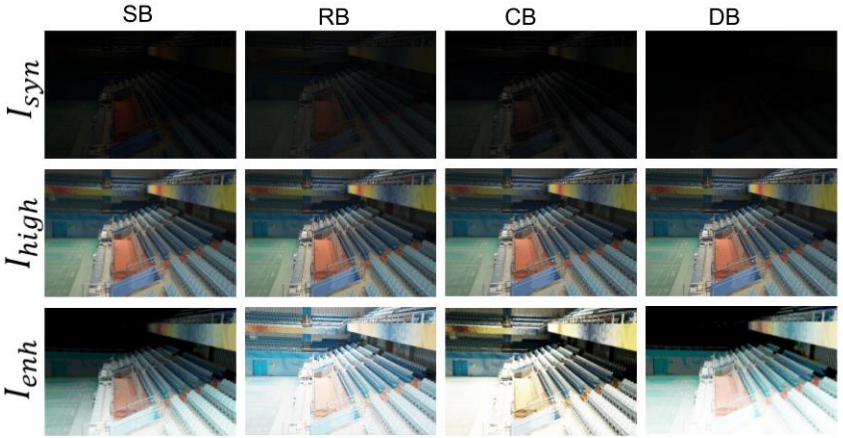


Figure: SB: Statistical-based, RB: Retinex-based, CB: Convolution-based, DB: Depth Estimation-based

PSNR and SSIM Values

Table: Quantitative Ananlysis Of Four Methods.

Methods	**PNSR**	**SSIM**
Statistical-based Method (SB)	**20.6359 dB**	**0.8429**
Retinex-based Method (RB)	8.7808 dB	0.2256
Convolution-based Method (CB)	9.1096 dB	0.5280
Depth Estimation-based Method (DB)	7.8940 dB	0.1586

Conclusions and Future Scope

Conclusion

The employed Statistical, Retinex, Convolution, and Depth Estimation based Methods have successfully generated low-light images, and showcased significant advancements in low-light image enhancement.

Future Scope:

The focus will be on working more towards enhancement and incorporating additional datasets for comprehensive analysis.

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Thank You