School

of

Electronics and Communication Engineering

Mini Project Report

on

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

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Semester: V, 2023-2024

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2023-2024

SCHOOL OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

This is to certify that project entitled **"Generation of synthetic low-light images using physics-based methods towards enhancement"** is a bonafide work carried out by the student team of **"P Yashaswini (01FE21BEC050), Rakshita K Joshi (01FE21BEC042), A S V Dheeraj (01FE21BEC161)**. The project report has been approved as it satisfies the requirements concerning the mini project work prescribed by the university curriculum for BE (V Semester) in the School of Electronics and Communication Engineering of KLE Technological University for the academic year 2023-2024

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ACKNOWLEDGMENT

The successful culmination of our venture into the Generation of synthetic low-light images using physics-based methods towards enhancement owes its triumph to the gracious support of many individuals. As a cohesive unit within the Centre of Excellence in Visual Intelligence [CEVI], we extend our warm thanks to each contributor who has helped us with our project. The Team expresses its profound appreciation to Prof. Sunita Budihal, Head of the Department at the School of Electronics and Communication, for allowing us to extend our skills in the direction of this project. The team expresses heartfelt gratitude to our guides, Uma Mudenagudi and Ramesh Ashok Tabib, whose wisdom and expertise played a pivotal role in steering the project toward success. In acknowledging their collective efforts, we deeply appreciate the assistance received from everyone, recognizing their vital role in bringing this project to fruition.

By:

Team

ABSTRACT

This proposal introduces the Generation of synthetic low-light images using physics-based methods, designed to enhance images in challenging low-light conditions. Leveraging principles from optics, radiometry, and image processing, our proposed equation seeks to authentically replicate natural low-light scenes. Often, capturing genuine low-light images, each with its corresponding ground truth is extremely challenging. To overcome this problem a lot of learning-based synthetic low-light image-generating models have been put out to generate low-lit image datasets with ground truth. However, these models often neglect the intrinsic properties of the scenes depicted in the images. To address this limitation, our solution advocates for a physics-based synthesis of low-light images, offering a more nuanced and context-aware approach to image enhancement. Unlike existing learning-based synthetic models, our method considers the inherent characteristics of the scenes, ensuring a more faithful representation of natural low-light scenarios. The synthesized low-light dataset plays a pivotal role in training the state-of-the-art light enhancement model, a versatile tool which is used in various applications like surveillance, 3D reconstruction and many more.

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Chapter 1

Introduction

In the era of information technology, images play a vital role in daily life and work. However, challenges such as low ambient light often result in images with insufficient brightness, reduced clarity, and colour distortion. These limitations can lead to the loss of valuable information within the images. To address this, advancements in image enhancement technologies are crucial for mitigating these issues and ensuring the effective conveyance of information. Embracing such innovations is key to unlocking the full potential of visual content in our technologically driven world.

1.1 Motivation

With the development of machine learning, some low-light image enhancement models based on deep learning have shown good performance. Most of these models use learning-based synthetically generated models to train and test their models as it is how the registration of the image is maintained in both low light and bright light images which don't need pre-processing.

Nonetheless, challenges emerge in the realm of learning-based rendering. Issues such as colour distortion, over-smoothing, blurriness in rendered images, training data bias, and inconsistency in illumination levels can arise.

Physics-based methods of synthetically generating low-light images stand out as comprehensive solutions to a multitude of challenges. By embodying the governing laws of nature, these models inherently encapsulate fundamental concepts such as time, space, causality, and generalizability. This unique approach ensures that the model goes beyond mere learning from examples; it acquires the capacity to apply its profound understanding to novel and unforeseen scenarios. Armed with a foundation rooted in the principles of physics, these models exhibit adaptability, making them notably robust and proficient in navigating a diverse array of real-world challenges. Whether it's the intricacies of light interactions, the complexities of diverse environments, or the nuances of different lighting conditions, physics-based models demonstrate a remarkable capability to comprehend and simulate these factors with a level of realism and versatility that sets them apart.

1.2 Objectives

- Synthetic low-light image generation using physics-based methodology.
- Evaluation of enhancement methods through generated data.

- Performance comparison with state-of-the-art methods on benchmark datasets.

1.3 Literature survey

- **Instant Dehazing of Images Using Polarization - 2001 (IEEE Access)**

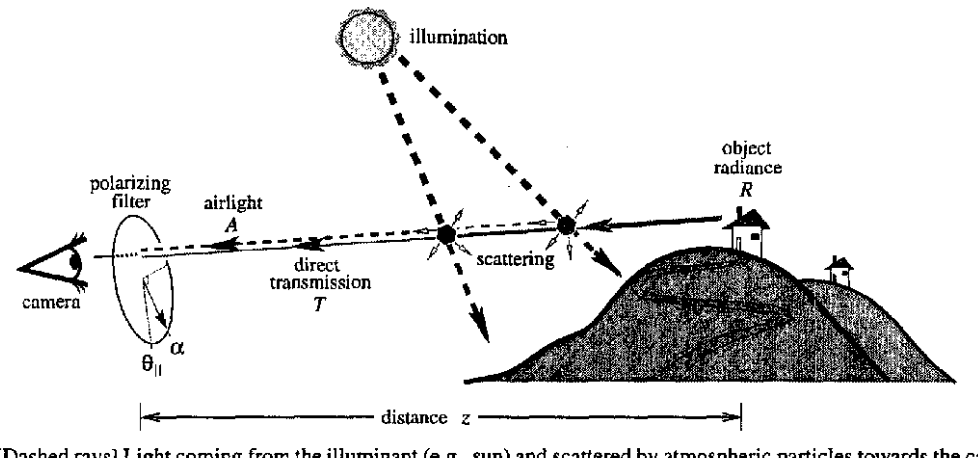

Figure 1.1: Working of the Polarization Method

  - In this paper[8],The study describes a method for instantly removing haze from images using polarization. This method can be applied to images taken in poor visibility conditions and provides improved scene contrast and color. It also yields a range map of the scene and information about atmospheric particles.

- **Contrast Restoration of Weather-Degraded Images - 2003 (CVPR)**
  - This paper [2] focuses on physics based model
  - Uses two atmospheric models 1) Attenuation and 2) Airlight
  - Attenuation: The way the light gets attenuated as it traverses from scene point to the observer. Loss of brghtness of light due to atmosphere.
  - Airlight: It says how a column or part of atmosphere act as a light source by reflecting to the observer.
  - Contrast Restoration of iso-depth images
    * Gave the formula for pixel intesity
    * Taken two adjacent pixels with same depth from scene point and gave two formulas for pixel intensities respectively
    * Then they considered for all the pixels
    * Repeated the same for all depths
  - They did contrast restoration of iso depth images
  - After this they could make out depth edges and reflectance edges, also depth discontinuities from two images captured under different weather conditions.

- They took varying depth and did contrast restoration for scene structure where depth changes abruptly.
- For only monochrome images

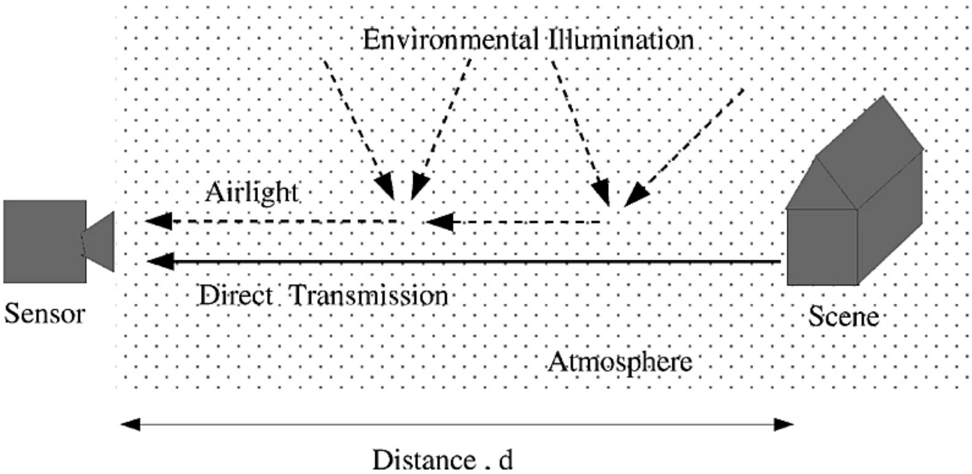

Figure 1.2: Flowchart of RetinexNet

- **Polarization: Beneficial for visibility enhancement - 2009 (CVPR)**
  - In this paper[9] the author compared the different polarization methods for low light enhancement of images.
  - Mounting a polarizer attenuates the signal associated with the object and this attenuation degrades the image quality.
  - Under the constraint of equal acquisition time, using a polarizer is beneficial for enhancing the SNR only when the degree of polarization(DOP) ¿ 0.5 but in nature DOP is less than or equal to 0.75.
  - Thus, a polarizer is beneficial only for airlight[9] ¿ 2/3, which corresponds to an optical depth of b = 0.36.
  - Therefore, in conclusion, the author states that for any DOP, in the range b ¡ 0.36, it is never worth using a polarizer, for enhancing the SNR under the constraint of equal acquisition time.
- **Histogram-based Image Enhancement for Non-uniformly Illuminated and Low Contrast Images - 2015 (ICIEA)**
  - In this paper[5], This survey examines various methods for enhancing the low-contrast image, including histogram techniques,fuzzy-based approaches, and mathematical morphology-based methods, highlighting ongoing debate regarding their ability to consistently produce well improved images

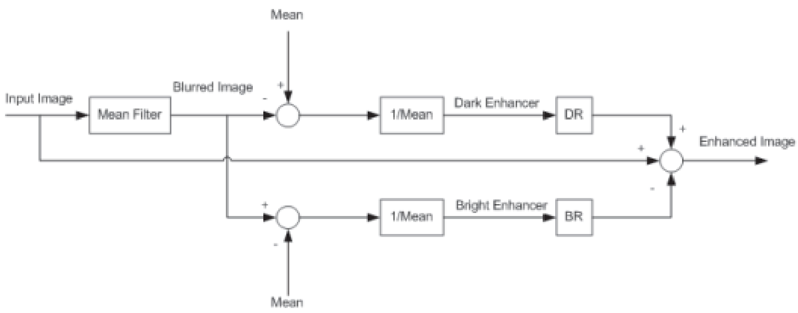

Figure 1.3: Flowchart of the Proposed Model

- **Contrast Enhancement of Low-light Image Using Histogram Equalization Illumination Adjustment - 2018 (ICEIC)**
  - In this paper [1] they have evaluated low light image enhanced method ny naturalness image quality evaluator(NIQE) and colourful-based patch-based contrast quality index(CPCQI)
  - They have compared their model with typical HE method by measuring quality of images.
  - One method proposed earlier was decomposition method that decomposed an image into reflectance and illumination. Then enhanced illumination layer. But this is slow process. So they applied this process after HE
  - Gaps - They have approximated the value of gamma. But it should optimal value of gamma for different kind of low light image.

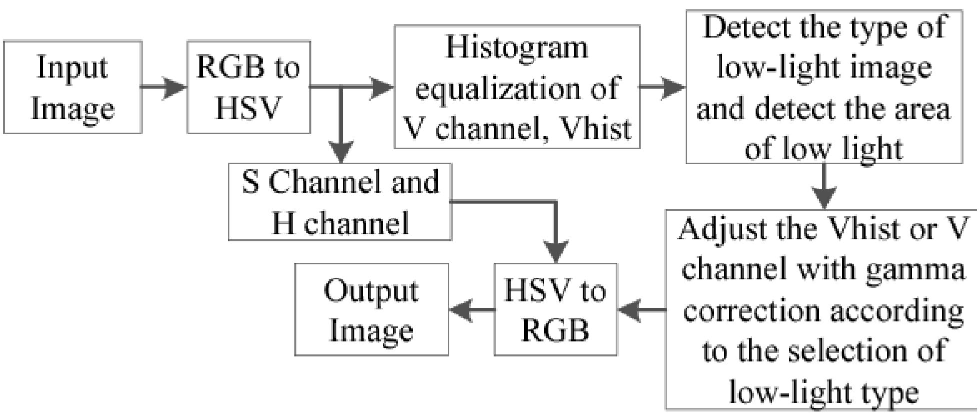

Figure 1.4: Flowchart of RetinexNet

- **Deep Retinex Decomposition for Low-Light Enhancement - 2018 (CVPR)**

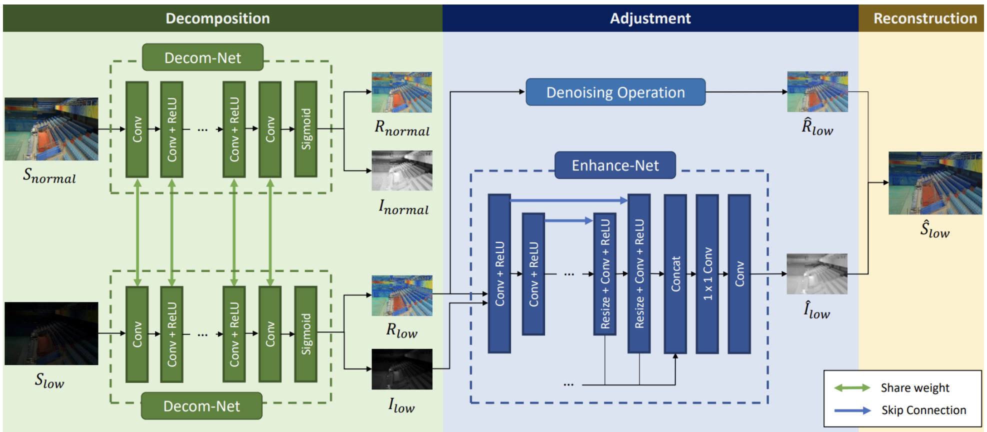

Figure 1.5: Flowchart of RetinexNet

  - The paper[11] introduces a deep learning method called Deep Retinex Decomposition for enhancing low-light images.
  - As in fig 1.5, the method utilizes a network called Retinex-Net, which consists of two sub-networks: Decom-Net and Enhance-Net where Decom-Net is responsible for decomposing the input image into reflectance and illumination components and Enhance-Net adjusts the illumination map to maintain consistency at large regions and tailor local distributions.
  - The contributions of the work include the construction of a large-scale dataset with paired low/normal-light images and the development of a data-driven image decomposition method.

- **Low-Light Maritime Image Enhancement with Regularized Optimization and Deep Noise Suppression - 2020 (IEEE Access)**

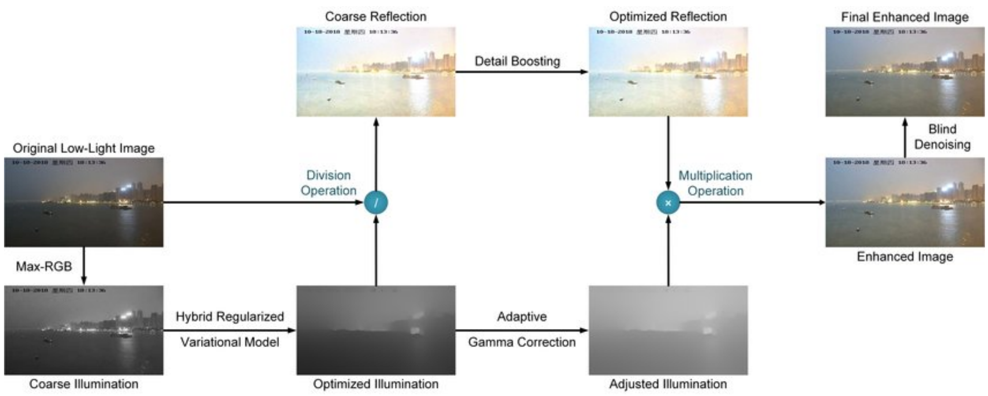

Figure 1.6: Flowchart of the Proposed Model

  - In this paper[3], the authors have proposed to enhance the low-light images through regularized illumination optimization and deep noise suppression.

- As in the fig 1.6, a hybrid regularized variational model was used, which combines L0-norm gradient sparsity prior with structure-aware regularization and is presented to refine the coarse illumination map originally estimated using Max-RGB.
- The authors propose a two-step framework for low-light image enhancement based on the Retinex theory, which benefits from regularized illumination optimization and deep blind denoising.

- **Histogram-Based Transformation Function Estimation For Low-Light Image Enhancement - 2022(ICIP)**

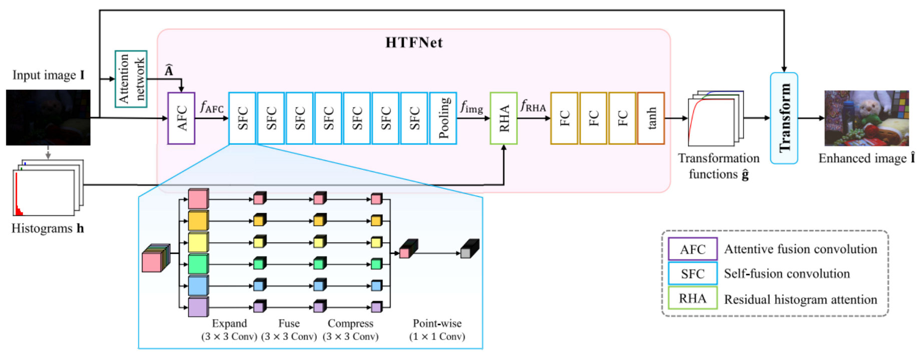

Figure 1.7: Proposed algorithm of HTFNet model

- In this paper[6],The study talks about traditional low-light image enhancement, introduces HFTNet as a novel algorithm, and demonstrates its superior performance over current techniques.

1.4 Problem statement

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

1.5 Application in Societal Context

Enhancement of images captured in low-light conditions is one of the requirements in present societal conditions.
1. Security and Public Safety
Improved low-light image quality enhances the ability of surveillance systems to detect and identify potential security threats in dimly lit areas, such as parking lots and public areas.
2. Traffic Management
Improved low-light image quality can be applied to improve surveillance for traffic monitoring and management. This aids in enhancing public safety and improving overall traffic flow.
3. Search and Rescue
Enhanced visibility during nighttime operations enables law enforcement agencies to gather more accurate and reliable evidence, aiding investigations and ensuring public safety.

Chapter 2

System design

In this chapter, we will be looking towards the functional block diagram and the final design which is being implemented.

2.1 Functional block diagram

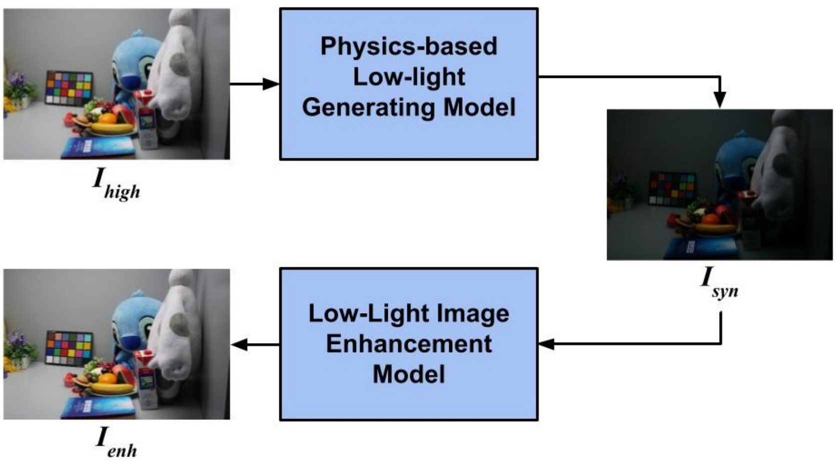

Figure 2.1: Overall framework to genrate synthetic low-light image towards enhancement.

Well-lit image is the input to the physics-based synthetic low-light image-generating model. The generated low-light image dataset is used to train the light enhancement model to evaluate the efficiency of the synthesis.

2.2 Final design

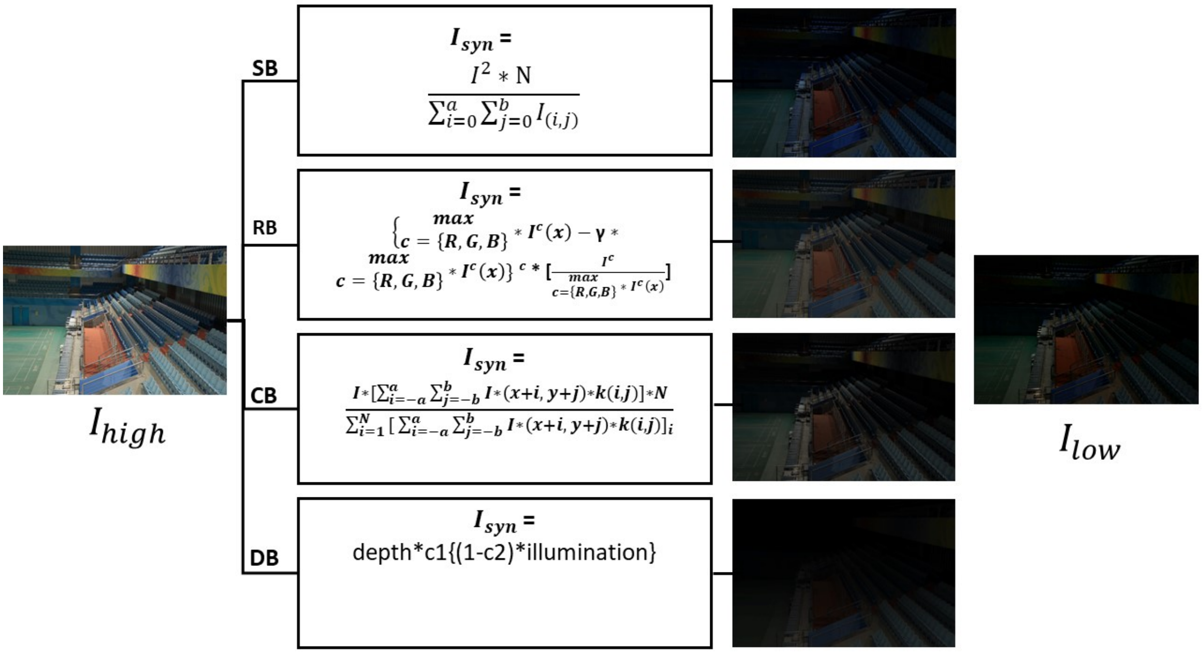

Figure 2.2: Physics-based mathematical equations of all the four proposed methods

Chapter 3

Implementation details

In this chapter, we will look into the final system architecture's specifications and the proposed architecture's algorithm.

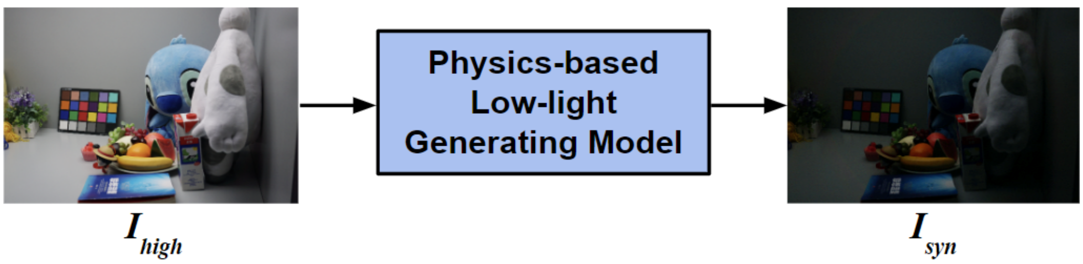

Figure 3.1: Block diagram to generate synthetic low-light image

3.1 Specifications and final system architecture

The formulation of images captured in low-light environments is elegantly encapsulated through a mathematical model, as delineated in the equation below:

$$I(x, y) = R(x, y) \cdot L(x, y), \tag{3.1}$$

where symbolises$I(x, y)$ symbolizes the captured image at the pixel location specified by coordinates (x, y), $R(x, y)$ denotes the reflectance map, representing the proportion of light that is reflected by the object at the given pixel, and $L(x, y)$ signifies the illumination map, capturing the intensity of light present at each pixel.

This model crucially distinguishes between the intrinsic properties of the objects being imaged (reflectance) and the external lighting conditions (illumination). Traditional image enhancement methodologies endeavour to concurrently estimate these two components from a solitary observation, a task that presents considerable challenges due to the complex interplay between object reflectance and environmental lighting.

In the quest to refine the quality of low-light images, the literature introduces Retinex theory as a foundational approach. Specifically, the work cited as [12] advocates for the application of Retinex-based methods in the enhancement of images plagued by inadequate lighting. These methods excel by assuming that the colors of objects are consistent across varying lighting conditions, thus enabling the effective separation of the illumination effects from the inherent colours and textures of the image content. This separation facilitates the enhancement of the overall visibility and detail within low-light images, showcasing the potency of Retinex theory in addressing the challenges associated with low-light image processing.

Inspired by this equation we came up with four models:

3.1.1 Statistical-based Model

Figure 3.2: I_{high} represents bright light image, I_{ill} represents the corresponding illumination map of the image and $I_{syn,SB}$ represents the synthetically generated low-light image using Statistical-based method.

Our first approach is the Statistical-based Model. a simple method to enhance low-light images by estimating reflectance and reconstructing them with boosted intensity. Reconstructs the image by multiplying the original image with the estimated reflectance.

$$I_{syn} = I^2 * N / \sum_{i=0}^{a} \sum_{j=0}^{b} I_{i,j} \tag{3.2}$$

where I_{syn} represents the synthesised image, I represents the original bright light image, N represents the total number of pixels and a and b represents the aspect ratio of the image.

3.1.2 Retinex-based Method

Our second approach is the Retinex-based Method. This code implements an algorithm to improve low-light images based on the Retinex model. It estimates an illumination map, separates reflectance, and reconstructs the image.

1. Illumination map estimation: It calculates the maximum value across color channels for each pixel as an initial estimation.

2. Reflectance separation: It divides the original image by the illumination map to obtain the reflectance component.

3. Image reconstruction: It multiplies the illumination map by the reflectance to reconstruct the image.

$$I_{syn} = (\max_{c=\{R,G,B\}} I^c(x) - \gamma[\max_{c=\{R,G,B\}} I^c(x)])^c * [I^c / \max_{c=\{R,G,B\}} I^c(x)] \tag{3.3}$$

where I_{syn} represents the synthesised image, I^c represents the original three channel bright light image, N represents the total number of pixels γ represents the gamma correction co-efficient and R,G,B is the different channels in a three channel image.

3.1.3 Convolution-based Method

Our third approach is the Convolution-based Method:

$$I_{syn} = [I \cdot N \sum_{i=-a}^{a} \sum_{i=-b}^{b} I(x+i, y+j) \cdot K(i,j)] / \sum_{i=0}^{N} [\sum_{l=-a}^{a} \sum_{i=-b}^{b} I(x+i, y+j) \cdot K(i,j)]_l \tag{3.4}$$

where I_{syn} represents the synthesised image, I represents the original bright light image, N represents the total number of pixels a and b represents the aspect ratios of the image and $K(x, y)$ is the kernel.

Box blur almost satisfied the noises that occurred in the low light conditions. After taking the box blur with a 5x5 kernel, the same approach as the Stastical-based method was applied.

3.1.4 Depth Estimation-based Method

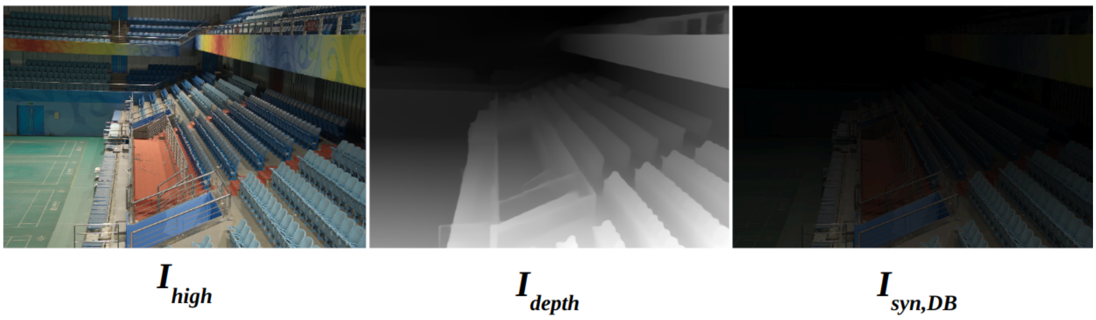

Figure 3.3: I_{high} represents bright light image, I_{depth} represents the corresponding depth map of the image and $I_{syn,DB}$ represents the synthetically generated low-light image using Depth Estimation-based method.

Our fourth approach is the Depth Estimation-based Method. A method using depth information to potentially improve low-light enhancement by adjusting illumination based on object distance.

1. Illumination Map: It estimates the illumination by finding the maximum intensity per pixel.

2. Reflectance Separation: It separates reflectance by dividing the original image by the illumination map.

3. Depth-based Illumination: It creates a new illumination map by multiplying the existing one with the depth image.

4. Image Reconstruction: It reconstructs two versions: one using the original illumination and one using the depth-aware version.

$$I_{syn} = depth * c1[(1 - c2) * illumination] \tag{3.5}$$

where I_{syn} represents the synthesised image, *depth* is the depth map of the input image, *illumination* is the illumination map of the input image, $c1$ is the effect of depth and $c2$ is the illumination co-efficient.

Chapter 4

Results and discussions

4.1 Dataset Description

- LoL Dataset
  - Training: 450 pairs
  - Testing: 35 pairs

Figure 4.1: First row represents low-light images and second row represents bright light images from the LOL dataset

4.2 Evaluation metrics

We evaluate the results of synthetically generated low-light image dataset using Kullback-Leibler Divergence (KL Divergence)[7] for two distributions p and q

$$KL = \sum p(x) ln \frac{p(x)}{q(x)} \tag{4.1}$$

We evaluate the results of enhanced low-light images using Peak Signal to Noise Ratio (PSNR)[4] and Structural Similarity Index Measure (SSIM)[10] evaluation metrics. **PSNR** is the measure of the power of corrupting noise that affects the fidelity of its representation and the ratio between the maximum possible power of signal, while **SSIM** is a comprehensive metric that measures image quality loss caused by the processing such as data comprehension or data transfer loss, and is a complete reference metric which requires the ground truth and the processed image. PSNR and SSIM are defined as:

$$PSNR = 10 log_{10}(\frac{P_{signal_{max}}}{MSE}) \tag{4.2}$$

where $p_{signal_{max}}$ is the maximum power of the signal

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4.3}$$

where $\mu_x \mu_y \sigma_x \sigma_y and \sigma_{xy}$ are means, standard deviations and covariances for two images x and y

4.3 Experimental Results

4.3.1 Experimental Results of Data Generation Methods

1. Experimental Results of Four Methods

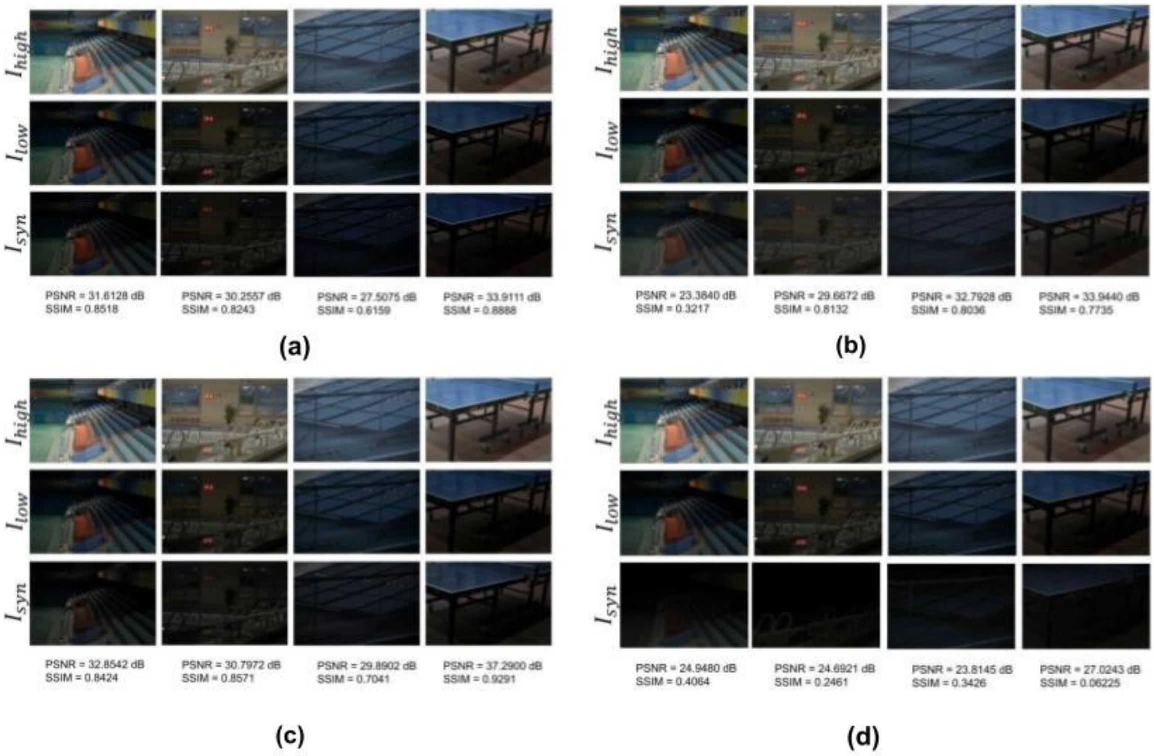

Figure 4.2: (a) represents results of statistical-based method, (b) represents results of retinex-based method, (c) represents results of convolution-based method, (d) represents results of dept estimation-based method.

where I_{high} represents bright light images from dataset, I_{low} represents low light images from dataset, and I_{syn} represents synthetically generated low-light images respectively with PSNR and SSIM values between synthetically generated low-light images and low-light images from the dataset.

2. Comparison Results of Four Methods

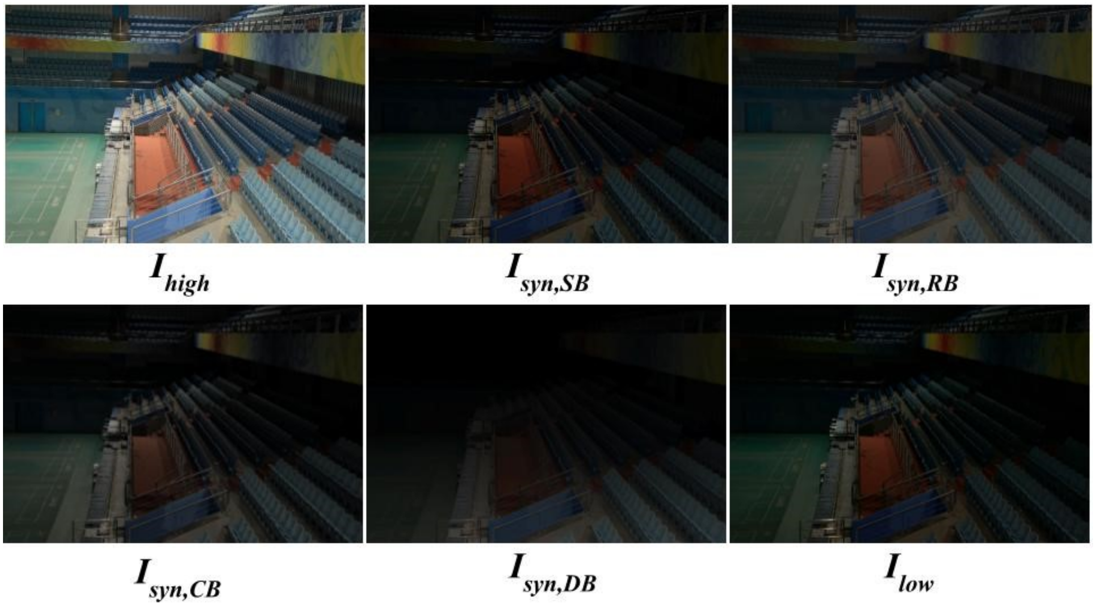

Figure 4.3: Comparison results of Statistical-based, Retinex-based, Convolution-based, Depth estimation-based methods

where I_{high} represents bright light image, $I_{syn,SB}$ represents synthetically generated low-light image using statistical-based method (SB), $I_{syn,RB}$ represents synthetically generated low-light image using retinex-based method (RB), $I_{syn,CB}$ represents synthetically generated low-light image using convolution-based method (CB), $I_{syn,DB}$ represents synthetically generated low-light image using depth estimation-based method (DB), I_{low} represents low-light image from dataset.

3. Histogram Comparison Results of Four Methods

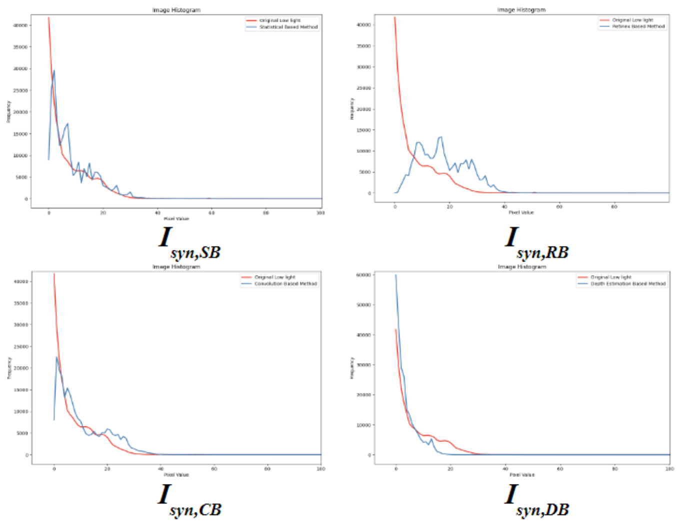

Figure 4.4: Histogram between low-light image and generated low-light image for four methods. SB: Statistical-based, RB: Retinex-based, CB: Convolution-based and DB: Depth Estimation-based

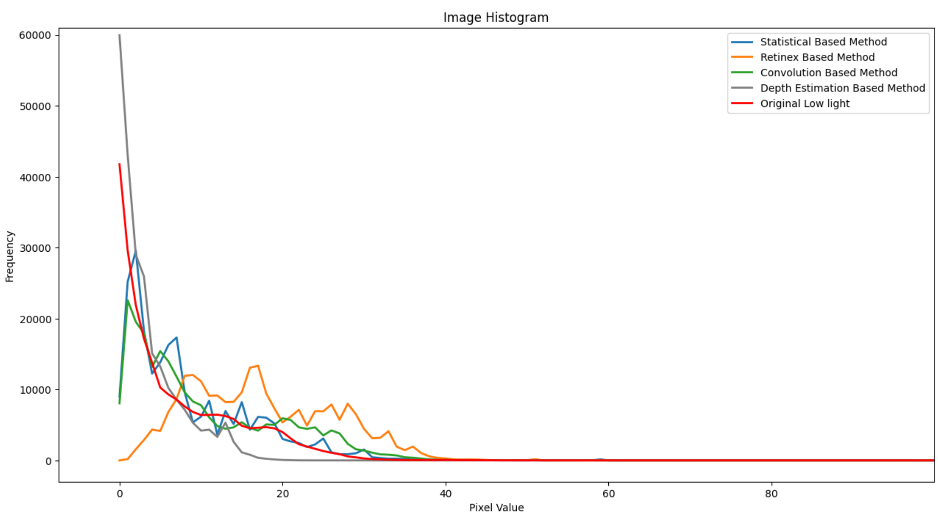

Figure 4.5: Histogram comparison of four methods

4. Kullback-Leibler Divergence Score

Table 4.1: 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**

4.3.2 Experimental Results of Image Enhancement

1. Experimental Results of Image Enhancement of Four Methods

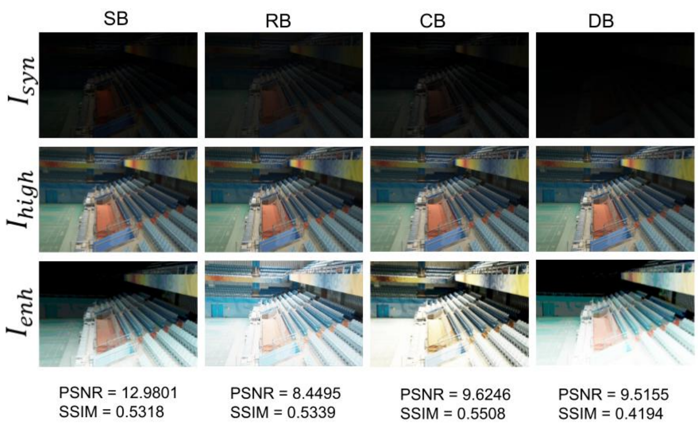

Figure 4.6: First row represents generated low-light images, second row represents bright light images and third row represents enhanced images of four methods SB: Statistical-based, RB: Retinex-based, CB: Convolution-based, DB: Depth Estimation-based

2. PSNR and SSIM Values

Table 4.2: Qunatitative Analysis For 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

Chapter 5

Conclusions And Future scope

5.1 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.

5.2 Future Scope

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

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