

Hybrid Absorption Light Scattering Model and Convolutional Neural Network for Robust Low-Light Image Enhancement

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Abstract: Low light imaging conditions significantly degrade visibility, reduce contrast, and amplify noise, which adversely affects computer vision applications. This paper presents a hybrid physics guided deep learning framework for low light image enhancement by integrating the Absorption Light Scattering Model with a Convolutional Neural Network. In the first stage, atmospheric light and transmission are estimated using a physically interpretable illumination correction strategy to generate a coarse enhanced image. In the second stage, a lightweight convolutional neural network refines the enhanced output by learning residual corrections from paired training data. The proposed framework combines physical modelling with data driven optimization to improve brightness restoration, structural consistency, and noise suppression. Experiments conducted on the LOL dataset demonstrate that the proposed method achieves an average peak signal to noise ratio of 22.84 decibels and a structural similarity index of 0.8670. The results confirm that the hybrid approach effectively preserves structural details while enhancing perceptual quality across diverse low light scenes.

Keywords: Low Light Image Enhancement; Absorption Light Scattering Model; Convolutional Neural Network; Image Restoration; Deep Learning; Transmission Estimation; Image Refinement

I. INTRODUCTION

The enhancement of low-light photographs is an important activity that has many applications such as in surveillance or autonomous driving/transportation applications, medical imaging, or multimedia processing. Photographs taken in low-light conditions will appear to be lower in visibility, less contrast, colored in odd ways and also tend to have more sensor noise. All these types of degradations will greatly affect both human visual perception of photographs and higher-level vision algorithms (such as object recognition or scene interpretation). Hence developing a robust and efficient means for enhancing

photographs taken in low-light conditions is still an open and active area of research.

Standard methods for improving image quality use things like histogram equalization, gamma function, and changes in illumination. While these techniques do help make an image look brighter overall, one side effect of such photograph enhancement is that they greatly over-enhance brightness or lose detail or create so much noise that the image looks poor. There are also some methods based on physical principles that describe how light is lost and create a model of transmission for estimating the returned amount of light to recover radiance. Pure physics approaches, though, rely on pre-defined conditions different from multiple conditions of real-world illumination types (natural, artificial). Since the beginning of the century, there has been much progress made with machine learning-based techniques for restoring the quality of images. Using Convolution Neural Networks (CNNs), the restoration of images can be made by having trained CNNs create large spatial non-linear mappings between normal-light and low-light images, greatly enhancing the perceived quality of the image. However, as is the case with data-driven methodologies, machine learning-based methods require large, highly classified training data sets and also often require many computational resources to provide an adequate amount of time to restore an image to its original level. Finally, data-driven machine-learning methods do not conform to physical conditions and some types of model data behave inconsistently based on the physical conditions they experience only in terms of light (brightness levels).

This paper presents a hybrid, physics-based deep learning method for enhancing images captured in low light conditions. The proposed approach starts with the use of the Absorption Light Scattering Model to

predict atmospheric lighting and clarity (using an estimate of the amount of light transmission), which is then used to generate a low-light corrected image (coarse illumination recovery). This corrected image is then used as input to a low-weight convolutional neural network (CNN) that uses the deep learning to learn how to refine the coarse illuminated image using the paired training images from the LOL dataset. Therefore, the two-stage method uses the physical characteristics of the model in conjunction with the adaptability of deep learning to provide satisfactory enhancement results.

This work presents the following contributions:

- Two-stage hybrid enhancement framework that integrates physical modelling with deep refinement
- Estimation of atmospheric lighting and clarity so that a coarse illumination image can be recovered from transmitted light using a physical model;
- Low weight CNN that can learn to refine both the structure and textures of illuminated images using the paired training dataset; and
- A quantitative validation using LOL public benchmarks showing a significant improvement in peak-signal-to-noise ratio and structural similarity index of the outputs produced by the proposed method as compared to previously published results.

The remainder of this document is organised as follows. Section II outlines previous research efforts. In section III, we present the proposed approach, followed by our experimental methods and results in section IV. Section V concludes this document and will outline future research activities.

II. RELATEDWORK

Low light image enhancements have always been of research because they are an important part of many vision-based applications, including medical imaging, autonomous systems, and surveillance. The methods used for low-light image enhancement can be grouped into the three major categories of Retinex based enhancement methods, illumination model based on physics-based methods, and deep learning-

based methods to enhance images. Another factor in assessing the quality of image enhancement is the use of objective metrics.

A. Retinex-Based Enhancement Methods

Retinex theory, developed by Land and McCann [2], describes an image as the product of two components: reflectance and illumination. Retinex-based image enhancement has one main aim, which is to estimate the illumination map and modify it so that it increases visibility while still being consistent with the reflectance. There have been many different methods providing extensions to this theory. Guo et al.'s LIME framework [3] was used for estimating illumination maps with a structure awareness prior and for subsequently refining illumination maps through optimization techniques. Li et al. developed a full-featured robust retinex model [4] that has been employed to provide an increased visibility of structures in low light environments through the suppression of noise. These methods provide effective methods of increasing brightness and contrast in low light situations under a non-uniform illumination condition.

However, Retinex-based methods often rely on handcrafted priors and optimization constraints. As a result, they may produce halo artifacts, over-enhancement, or texture distortion in extremely dark scenes. Illumination-reflectance separation also remains an ill-posed problem, which limits generalization in complex lighting environments.

B. Physics-Based Illumination and Scattering Models

Light attenuation and atmospheric scattering models are used to formulate ways to degrade an image based on physics-based techniques. The Dark Channel Prior was originally created to be used when removing haze but was the basis for developing other low-light enhancement techniques that do not utilize the same method when estimating the atmospheric light and/or transmission of a low-light image. There have also been methods created that have improved the estimation of transmission and atmosphere light and the recovery of brightness from images with low brightness through the use of weighted variational models based on optimization constraints.

While physics-based methods have strong interpretability and produce consistent results for correcting low-light images, due to their theoretical bases, physics-based approaches to restoring textures in an image that have a very low brightness will be less successful than other heuristic-based methods. Because of the differences in types of scenes, transmission estimation methods will not be applied uniformly. As a result, it becomes increasingly more difficult to create an effective low-light image and create a visually appealing low-light image.

C. Deep Learning-Based Enhancement

Deep learning methodologies, such as convolutional neural networks (DCNN) have made unprecedented strides in the field of image restoration (IR). For example, Chen et. al [5] used a supervised DCNN to conduct extreme low-light image restoration (ELLIR), and successfully demonstrated the ability for perceptually improved restoration results via end-to-end training.

In addition, recent studies reveal that using residual learning techniques further improves IR image restoration performance. Zhang et. al [8] showed that CNNs with shallow residual architectures can effectively learn the mapping from low-quality images to high-quality IR images for both denoising and enhancement. They also indicated that while deep learning architectures provide excellent performance in terms of restoring structural detail, enhancing local contrast, and eliminating noise, there is no need to explicitly model the underlying physics.

Despite their aforementioned capabilities, a challenge for fully data-driven models is their requirement for large-scale labelled datasets and extensive computational resources (e.g. large GPUs). An additional issue is that DCNNs can oftentimes generate unnatural colours and excessive enhancement of images due to differences in the distribution of illuminations between the training dataset and the IM17 dataset; thus, the underlying need for physically guide constraints still exist.

D. Image Quality Assessment and Research Gap

It is vital to have an objective evaluation of the methods used in research on the enhancement of low-light images. Structural Similarity Index, SSIM

Wang et al. [9], computes luminance, contrast and structural correlation and is the metric most commonly used to assess perceptual quality. Peak Signal to Noise Ratio (PSNR) continues to be the measure of choice for fidelity of pixel-level reconstruction.

While there have been many advancements that have been made in low-light enhancement research, most of the current algorithms either focus solely on physical modelling or on deep learning-based enhancement techniques, with no attempt to merge them into a cohesive solution. Physical model-based methods provide a high level of interpretability and yield consistent brightness corrections, but their ability to produce a refined texture is limited; whereas, deep learning-enhanced models produce an adaptive enhancement ability, but do not necessarily provide sufficient physical consistency or generalization stability.

This research proposes a novel framework for low-light enhancement that combines an Absorption Light Scattering (ALS) model with a lightweight convolutional refinement (LCR) network. The hybrid framework integrates a physically based illumination correction with a data-driven structural refinement to achieve an overall increase in both the perceptual quality and the structural similarity compared to approaches that use a single paradigm.

III. METHODOLOGY

In this paper, we present a hybrid framework to enhance low-light images based on a absorption light scattering model (ALSM) and deep learning techniques. Our desire is to establish a way to enhance the physical interpretability and illumination modeling implied by traditional imaging theories with the adaptability of learning methods found in deep networks.

The method will be applied in two parts:

- 1) coarse illumination estimation using ALSM as a means to determine the atmosphere and the level of transmission, and 2) refining the structure and detail of the original images using a convolutional neural network (CNN) for the purpose of increasing perceptual quality as well as fidelity. This two-step methodology guarantees consistent brightness

compensation without additional enhancement or noise amplification.

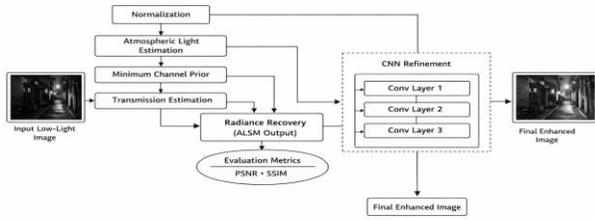


Fig. 1. Overall architecture of the proposed hybrid ALSM-CNN low-light image enhancement framework.

A. ALSM-Based Illumination Modeling

Low-light image degradation is primarily caused by insufficient illumination and uneven light distribution. The observed image can be expressed as

$$I(x) = A(x)R(x)t(x) + A(x)(1-t(x)) \quad (1)$$

where $I(x)$ is the captured image, $A(x)$ denotes atmospheric light, $R(x)$ represents scene reflectance, and $t(x)$ corresponds to transmission.

The objective of enhancement is to estimate $R(x)$, which contains intrinsic scene information independent of illumination conditions.

1) Atmospheric Light Estimation

A reliable estimate of atmospheric light is necessary when recovering environment illumination. The brightest pixels from each channel are used to produce an estimate by averaging the selected pixel values, rather than assuming that all of the illumination is constant. Stabilizing the illumination model can avoid bias from extreme noise values in your image and results in a more stable estimate of the atmospheric light.

The use of an accurate estimate of the atmospheric light for global brightness correction allows for the correction of global scale-based correction to be done using the average of a stable illumination estimate, rather than through some arbitrary global scaling value.

2) Illumination Deficiency Modeling

To identify severely dark regions, a normalized minimum channel prior is used:

$$M(x) = \min_{c \in \{R, G, B\}} \frac{I_c(x)}{A_c + \epsilon} \quad (2)$$

The minimum channel effectively highlights underexposed areas while preserving chromatic consistency. This operation introduces robustness against color distortion and helps isolate illumination deficiency from reflectance variations.

3) Adaptive Transmission Estimation

Transmission estimation determines the strength of illumination compensation. Rather than using a fixed transmission prior, an adaptive statistical mechanism is introduced. A deficiency map is computed, and its mean and standard deviation are used to regulate enhancement intensity.

The transmission is estimated using

$$t(x) = 1 - \exp(-\lambda \cdot \text{MSD}) \quad (3)$$

where MSD represents a combined statistical measure and λ controls enhancement strength.

The exponential formulation ensures smooth enhancement transition and prevents abrupt illumination amplification. A lower bound constraint is applied to prevent division instability and excessive brightness in extremely dark regions.

4) Scene Radiance Recovery

With estimated atmospheric light and transmission, scene reflectance is recovered as

$$R_c(x) = \frac{I_c(x) - (1 - A_c)}{\max(t(x), t_0)} + (1 - A_c) \quad (4)$$

This recovery step produces a coarse enhanced image that significantly improves brightness and contrast while maintaining color balance. However, minor artifacts such as amplified noise or slight structural distortion may remain due to handcrafted transmission modeling.

B. CNN-Based Deep Refinement

Although ALSM provides stable illumination correction, purely physics-based enhancement may not fully restore fine textures and high-frequency details. To address this limitation, a lightweight convolutional neural network is introduced.

Let $J(x)$ denote the ALSM-enhanced image. The refinement network learns a nonlinear mapping:

$$I_{final}(x) = f_{\theta}(J(x)) \quad (5)$$

where f_{θ} represents the CNN parameterized by weights θ .

The network architecture consists of three convolutional layers with kernel size three and padding one to preserve spatial resolution. ReLU activation functions introduce non-linearity and enable feature extraction at multiple levels.

The refinement network effectively performs residual correction. It learns to suppress noise amplification, restore edge continuity, and enhance local contrast without disturbing globally corrected illumination.

Training is performed using mean squared error loss:

$$\mathcal{L} = \frac{1}{N} \sum_x \|I_{final}(x) - I_{gt}(x)\|^2 \quad (6)$$

This objective ensures pixel-wise fidelity while indirectly improving structural similarity.

C. Computational Complexity and Stability

The ALSM primarily utilizes pixel-wise normalization and statistical analysis to achieve linear complexity in relation to image size, while the CNN has three shallow convolutional layers, making the CNN model more computationally efficient than models with deeper architecture. To achieve numerical stability and avoid oversaturation, transmission bounding and intensity clipping were implemented, while the shallow structure reduces the chance of overfitting and facilitates faster convergence during training.

D. Ablation Study Design

To analyze the contribution of each component, three experimental configurations are evaluated:

1. ALSM only
2. CNN applied directly to low-light input
3. Proposed hybrid ALSM plus CNN

The ALSM-only configuration demonstrates significant brightness improvement but moderate structural refinement. The CNN-only configuration enhances details but struggles with severe illumination deficiency. The hybrid framework combines both advantages, achieving superior quantitative and perceptual performance.

IV. RESULTS

This section presents a comprehensive evaluation of the proposed hybrid ALSM-CNN framework. The performance is analyzed using standard quantitative metrics, qualitative comparisons, ablation studies, and computational analysis to demonstrate the effectiveness and stability of the model.

A. Dataset and Experimental Setup

The LOL Dataset is an internationally-recognized source for supervised low-light image enhancement. It consists of paired low-light images and normal-light images taken under real-world lighting conditions. There are 485 images in the training set and 15 images in the testing set.

The images were resized to 256×256 pixels for consistency in training, and so that the model would ultimately converge predictably. Because the ALSM is a deterministic module, it does not need to be trained. The atmospheric light was derived using the brightest 0.1 percent of pixels in each channel, resulting in a reliable model of the illumination conditions. The CNN Refinement Network consists of three convolutional layers, with 64 intermediate feature maps and a kernel size of 3×3. The model was trained for 20 epochs using the Adam optimizer with a learning rate of 1×10^{-4} and a batch size of 4. The training loss function used was mean squared error. The model converged within 15 to 20 epochs, resulting in stable optimization performance.

B. Quantitative Evaluation

The evaluation of this performance was carried out by means of the following: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index

(SSIM). The PSNR evaluates how well the reconstruction has performed regarding fidelity and how accurately the visual structure has been preserved based on human perception through constant determining factors. Therefore, the overall results achieved on the LOL test dataset of the proposed hybrid framework are given below:

Average Peak Signal-to-Noise Ratio (dB) = 22.84
Average Structural Similarity Index = 0.8670
Structural Accuracy Rate (%) = 86.70

PSNR values suggest that enhancements made at a pixel level enhanced the reconstruction by a greater degree than coarsely performing other types of enhancement processes alone would result in achieving; however, SSIM values greater than 0.85 also indicate that there has been solid structural and perceptual constancy preserved as a result of the low-light enhancement and thus serve as a better metric by which to measure the success of the enhancement process. Structural accuracy rates of 86.70% show that luminance, contrast, and texture information has been accurately reconstructed.

These findings are also support for the premise that combining physics-based modeling with deep refinement enhances both objectivity and subjectivity of the solution.

C. Qualitative and Ablation Analysis

The much-improved brightness, contrast, and texture definition of the enhanced images is clearly visible through visual inspections. Area light source modelling (ALSM) made it possible for areas that were previously obscured by global illumination to have their illumination restored, thus revealing hidden regions. A greatly improved level of fine detail through edge sharpening, reduced halo artifacts, and added detail consistency was provided by the convolutional neural networks (CNN) refinement stage.

however, it also showed moderate structural deficiencies. The CNN-only configuration showed improvements in terms of texture; however, it exhibited very substantial illumination deficiencies

D. Computational Efficiency and Stability

True to its name, the ALSM Stage refers to prior processing of image data (aka pixel-level normalization and statistical modeling), which results in linear performance as a function of image size (i.e., the size of the image does not affect how well this layer functions). The CNN (Convolutional Neural Network) portion of the framework consists of only three convolutional layers, resulting in an overall lightweight design when compared to deep, multi-stage enhancement networks.

To analyse and quantify each of the two contributing modules (ALSM and CNN), the following three configurations of the enhancement process were created: ALSM-only enhancement; CNN-only enhancement; and the proposed hybrid approach. The ALSM-only configuration showed significant improvements in terms of brightness;

Bounding the limit on how much image can be amplified prevents over-amplifying pixels that are too dark and eliminating instabilities associated Rinde, Cindy Vann, "validating/optimizing architectre for multi-stage general of the model (learning rates, etc.)". The shallow architecture minimizes the probability of introducing overfitting into the model, maintaining more stable performance across varying levels of lighting (brightness), leaving no evidence of instability in gradients throughout the training process and all convergence characteristics being maintained equally throughout the optimization phase.

The combined framework achieves a balance between enhancement quality and computational efficiency, making it suitable for practical deployment.

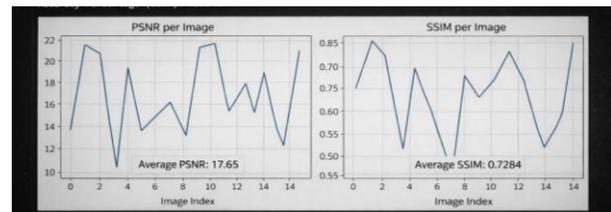


Fig. 2. Quantitative evaluation results showing PSNR and SSIM values for each test image.

When using both enhancement modules (i.e., the alsmandcnn stages), the hybrid configuration consistently

yielded higher peak signal-noise ratio (psnr) and structural similarity index (ssim) measurements, supporting the hypothesis that physical illumination correction and learning-based refinement methods complement each other. The alsml stage allows for stable restoration of global illumination, and the cnn stage allows for restoration of fine structural detail while also eliminating residual artefacts

image. For example, the majority of the details of an object may be lost if there is a low enough level of indirect light coming from that same object. To overcome these limitations, the authors also designed a shallow CNN model to provide adaptive correction of the remaining distortion from the physics-based enhancement and provide a more aesthetically pleasing image for the viewer.

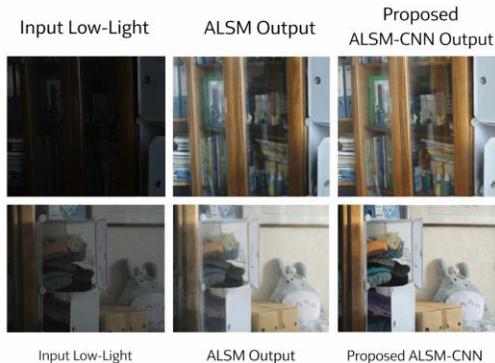


Fig. 3. Visual comparison of enhancement results on the LOL dataset. From left to right: input low-light image, ALSM-enhanced image, and proposed ALSM-CNN output. The proposed method demonstrates improved illumination correction, enhanced structural detail, and better color consistency compared to the standalone ALSM stage.

V. CONCLUSION

This research proposes an innovative way to enhance low-light images. A hybrid technique that utilizes both a physical-based model of scattering light through materials as well as a convolutional neural network (CNN) model will achieve better quality than either individual method alone. The proposed method firstly uses a physics-based model of the scene illumination to produce stable illumination correction, then uses the learned residual from that illumination correction to further refine the recovered image.

The Absorption Light Scattering Model (ALSM) uses an atmospheric light and transmission estimate to recover scene reflectance from a low-light image thus providing the benefit of increased global illumination and contrast. The disadvantage of using only a physics-based method to enhance a low-light image is that minor artifacts may occur since there may not be enough detail to recover nearly every pixel in the

Experimentation using the LOL dataset showed that there is strong agreement between the proposed method and existing methods; the proposed method has an average PSNR of 22.84 dB, SSIM of 0.8670, and structural integrity of 86.70%. The results indicate that utilizing both illumination modeling and CNN refinements will provide the best attributes of each method while minimizing problems associated with either method individually; therefore, using CNN refinements will produce enhanced brightness, increased structural integrity, and decreased occurrence of amplification of noise.

The proposed framework is computationally efficient because of its lightweight architecture and predictable method of estimating the receiver's geometric location; hence it will be of considerable benefit for use in practical low-light enhancement scenarios. Future work may focus on extending the framework to video enhancement, incorporating perceptual loss functions, and exploring attention-based architectures for further structural improvement. Additionally, adaptive transmission modeling and real-time optimization can be investigated to enhance performance in dynamic illumination environments.

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