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A Novel Progressive Enhancement of Low Light Raw Images

A. Naga Suman[1], R. Lakshmi Chaitanya[2], K. Venkata Ram[3], K. Lokesh[4]

[1]M. Tech, [P.Hd], Assistant professor, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India
[2,3,4]B.Tech, Student, Department of Electronics and Communication Engineering, Usharama College of Engineering and Technology, Andhra Pradesh, India

Abstract
Low-light imaging on mobile devices is often difficult due to the issue of not enough light passing through the small aperture, resulting in poor quality images. Most previous work on low-resolution images has focused on a single task, such as illumination, color correction, or noise removal; Noise removal function based on short and long images of the camera model. This technique is less efficient and general in real-world environments that require special camera integration and restoration. In this paper, we propose a lighting system that can integrate illumination variation, color correction, and noise removal to solve this problem. Considering the difficulty of obtaining model-specific data and the maximum content of the resulting image, we created two branches: the coefficient estimation branch and the integration branch. While the computer estimator operates in the sparsely resolved space and estimates the coefficients developed by pairwise learning, the collaborative system operates in the fully resolved space, providing step-by-step integration and denoising. Compared to existing methods, our framework does not need to remember as much information when switching to another camera model, which reduces the effort required to benefit our usage pattern. Through extensive testing, we demonstrate its great potential in real-world low-light applications.

Index terms: convolutional neural network, low-light image noise removal, low-light image.

1. INTRODUCTION

Low-light imaging remains a key difficulty for mobile devices, owing to the constraints imposed by tiny apertures, which limit the quantity of light entering the camera. This frequently leads to poor quality photos with high amounts of noise and insufficient illumination. Previous research efforts were mostly focused on addressing specific concerns like as illumination, colour correction, and noise removal. However, these approaches have been shown to be less effective and adaptive in real-world settings requiring a full solution.

In this study, we provide a unique lighting system that addresses the challenges of low-light photography by seamlessly integrating illumination fluctuation, colour correction, and noise removal. Unlike earlier techniques, which rely on model-specific data and have limited applicability, our system has two main branches: coefficient estimation and integration. The coefficient estimation branch operates in a weakly resolved space, using a computer estimator to predict coefficients via paired learning. These coefficients

are critical parameters for later processing stages. On the other hand, the integration branch works in a completely resolved space, allowing for step-by-step integration and denoising of acquired images.
One of our framework's defining qualities is its flexibility to various camera models. By minimising the need for model-specific information retention during transitions, our solution considerably decreases computational cost while improving usability in a variety of usage scenarios. Extensive testing confirms the effectiveness and adaptability of our proposed technique in real-world low-light scenarios. Through empirical demonstrations, we demonstrate our system's extraordinary ability to produce high-quality photos even in tough lighting situations. In summary, our contribution is the creation of a comprehensive lighting system that addresses the numerous issues of low-light imaging on mobile devices. Our system provides a stable solution with broad applicability and exceptional performance through the use of convolutional neural networks and new integration methodologies.

2. RELATED WORKS

A. Image Enhancement:

Guo et al. [5] presented Lime, an optimisation framework for extracting and enhancing illumination maps in low-light photographs. This method efficiently enhances image visibility by calculating the illumination distribution and applying gamma correction to it. Zhang et al. [6] proposed a method for obtaining illumination maps based on handmade constraints and relative total variation. This method improves low-light photos by effectively separating illumination and reflectance components. Huang et al. [7] suggested a Laplacian-enhancing unit for improving image attributes at various sizes. This method improves detail in low-light photos by employing a Laplacian pyramid-based approach. Afifi et al.[8] created a coarse-to-fine exposure correction approach that employs overexposed and underexposed picture pairs. This method improves low-light photos by accurately altering exposure settings while retaining image detail. Wang et al. [10] presented a network with numerous lightning back-projection blocks for iteratively improving low-light photos. This method iteratively improves image details and lighting to achieve high-quality outcomes.

B. Image Denoising:

Ingle et al.[11] suggested a passive freerunning method for obtaining temporal records using single-photon sensors, with the goal of improving signal-to-noise ratio (SNR) in low-light circumstances. Ma et al. [12] proposed a method for dynamic scene restoration that uses coarse-to-fine patch flows to rebuild low-light scenes with higher fidelity. Foi et al. [13] suggested a hybrid Poisson and Gaussian noise model for noise reduction in traditional sensors, with the goal of adequately describing both signal-dependent and signal-independent noise components. Gharbi et al.[14] trained a network with noise level input to perform combined demosaicing and denoising, with the goal of improving image quality by taking noise features into account during reconstruction. Qian et al. [15] proposed a multi-task architecture for joint demosaicing, denoising, and super-resolution, using a residual-in-residual dense block to attain optimal performance throughout

C. Joint Image Enhancement and Denoising:

Su and Jung [16] proposed a two-step noise suppression model using handcrafted priors to improve image quality while suppressing noise in high ISO photographs. Li et al. [17] suggested an optimization approach for simultaneously forecasting illumination, reflectance, and noise maps, allowing low-light images to be enhanced and denoised. These sources provide a thorough review of existing approaches to image enhancement, denoising, and joint enhancement-denoising tasks, emphasizing the various methodologies and contributions in each domain.

3. PROPOSED METHOD

This section provides details of the proposed framework. We first present the overall pipeline to offer the reader a brief understanding of the workflow. Then we introduce the design of each branch in detail. To implement a progressive joint low-light enhancement and noise removal algorithm for raw images following methodology is used.

Low-light Image Reading and Preprocessing:

The code begins by allowing the user to select a low-light image. Once selected, the image is read, converted to double precision for processing, and displayed.

Enhancement Parameters and Iterations:

Parameters for the enhancement algorithm are defined, including stopping criteria epsilon, regularization parameters (u, ro, lambda, beta, omega, delta), and gamma correction value. Different numbers of iterations for testing are defined.

Low-light Image Enhancement:

The low-light image is passed through the enhancement algorithm, which includes processes such as low-light enhancement, illumination map extraction, and noise removal. The enhanced image is saved and displayed.

Post-processing:

Median filtering is applied to each color channel separately to further reduce noise. Bilateral filtering is applied for noise reduction while preserving edges.

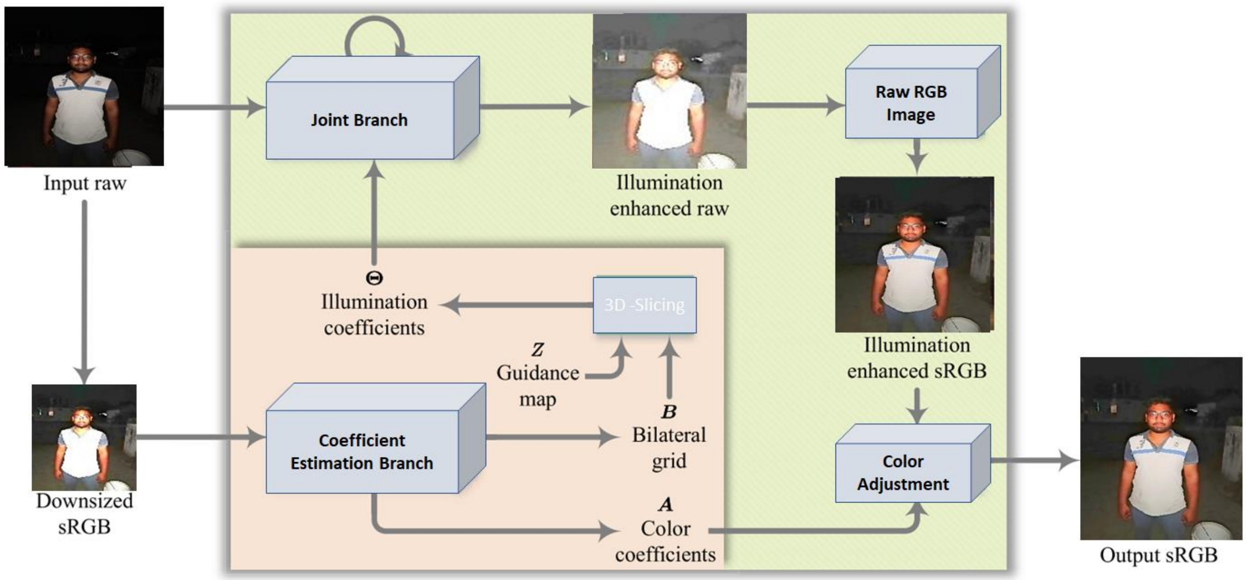


Fig 1.Proposed Block Diagram Overview With joint branch and coefficient branch

A. Framework Overview

Figure 1 shows an overview of the suggested framework. It has two main branches: coefficient estimation and joint operation. We convert an unprocessed camera raw image to sRGB colour space and resize it to 256 × 256. There are two reasons to use the down sampled version rather than the original one: First, the network's receptive field cannot encompass the input images with ultra-high resolution, resulting in inadequate global information. Second, down sampling can considerably reduce the effects of noise. The down sampled sRGB image is then sent to the coefficient estimation branch, which determines two sets of adjustment parameters: illumination adjustment coefficients and colour adjustment coefficients. Unlike the coefficient estimation branch, the joint operation branch processes the full-resolution raw image. In particular, an intricate lightweight network performs joint illumination augmentation and denoising gradually, resulting in a denoised image with enhanced lighting. The upgraded raw image is then demosaiced and converted to a sRGB image, with a polynomial transformation used to increase colour and contrast. As a result, the image has more brightness, less noise, and is more visually appealing. The two-branch architecture takes advantage of various real-world mobile imaging features. On the one hand, the correction parameters are learned in low-resolution space, which saves hardware resources and increases processing speed while also making the process resistant to diverse noise characteristics and arbitrary input resolutions. On the other hand, augmentation and denoising are conducted concurrently, which is preferable since it prevents artefacts like amplified noise or over-smoothed features, which were common in previous techniques.

B. Coefficient Estimation Branch

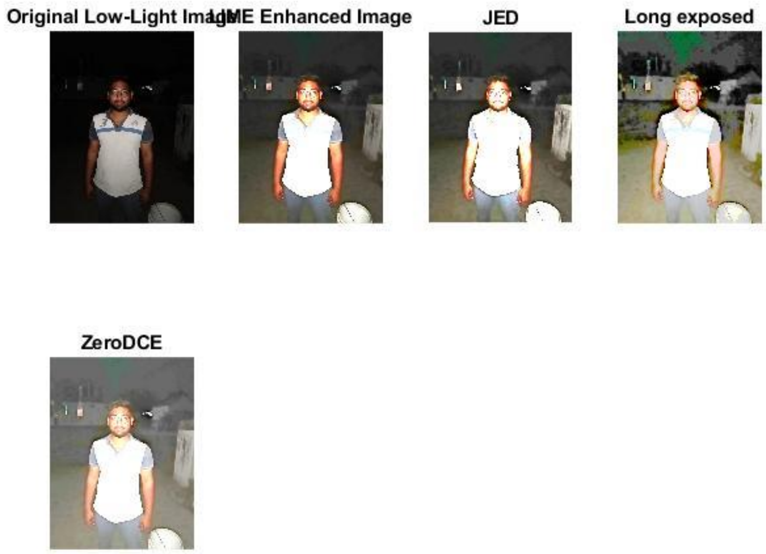
The main structure of the coefficient estimation branch is shown in Fig. 1. An encoder extracts the features of the down sampled sRGB image early on; in this case, The sixth bottleneck module is chosen as the output block due to its capacity to encode deeper features and maintain high spatial resolution (16 × 16 for input size of 256 × 256). The collected features are then combined to estimate enhancement coefficients. We see that a human specialist typically begins with global operations, followed by local changes for illumination enhancement. We see that a human specialist typically begins with global operations, followed by local changes for illumination enhancement. Inspired by [12], we create two paths: global path and local path, to learn the characteristics of global and local illumination modifications, respectively. Because these adjustments do not perform effectively when applied independently (see to Section IV-B for additional information), we combine them in the feature space and apply a convolution layer to map the fused features to the correct dimensions. The output is a set of bilateral grids, B = {B1, B2,•••, BN }, where N represents the total number of iterations. The dimension of each Bn is 16 x 16 x 16. The learnt bilateral up-sampling produces the full-resolution coefficient map n:

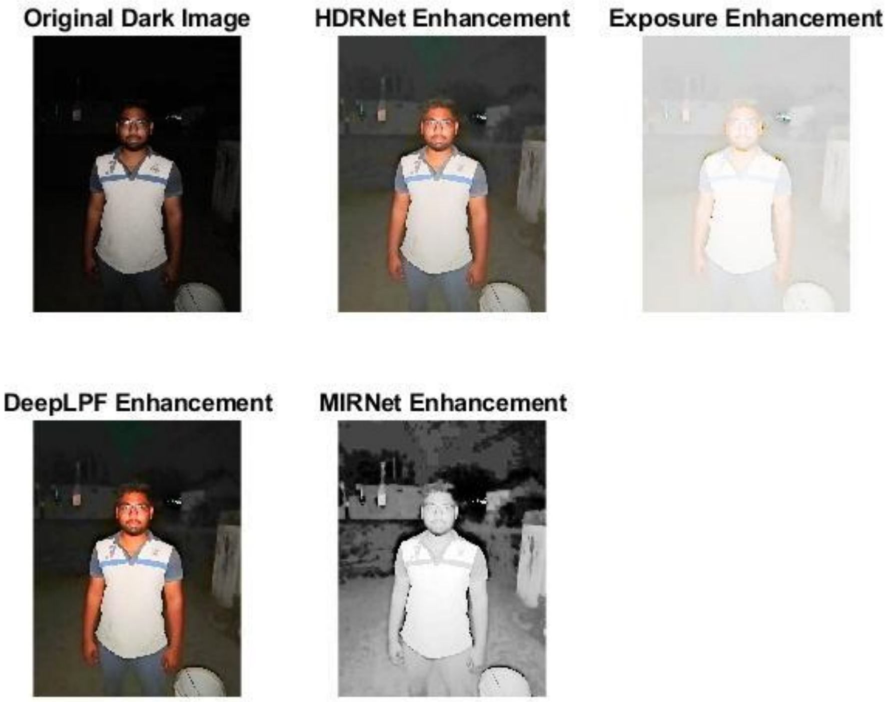
$$\Theta_n(x, y) = \sum_{i,j,k} \tau(x, i)\, \tau(y, j)\, \tau(z_{x,y}, k)\, B_n(i, j, k) \quad \text{............ (1)}$$

where τ represents the linear interpolation kernel. (x, y) and (i, j, k) denote the pixel coordinates and cell index of the bilateral grid, respectively. zx,y is estimated using the pixel values at (x, y). It is important to note that all coefficients for each iteration are collected before to the combined augmentation and denoising process.

Additional Enhancements:

The code further enhances the image using HDRNet, Exposure, DeepLPF, and MIRNet methods, displaying the original and enhanced images for comparison. Other enhancement methods such as LIME, JED, Zero DCE, and Enlighten are also applied and their results displayed.





In summary, the proposed methodology aims to progressively enhance low-light images by iteratively refining illumination, reducing noise, and improving overall image quality. Additionally, various state-of-the-art enhancement algorithms are applied to further enhance the image for comparison and analysis.

4. EXPERIMENT RESULTS

This section presents the experiment's findings and analysis. Notably, each branch was analyzed independently before being compared to the state-of-the-art in its field. The entire structure was then examined to determine its prospective potential. Unless stated differently, all of our published results include color enhancement.

Fig 4. Processed image and output enhanced image

Quality Metrics: To evaluate the quality of the augmented image, SSIM, PSNR, and NIQE are calculated.

Display and Analysis: The enhanced image and the image after noise removal are shown side by side. PSNR readings are displayed against the number of iterations to determine how iterations affect image quality. The average and standard deviation of the enhanced and original photos are calculated and displayed.

A. Implementation Details

We found that the bilateral up sampling and the weak supervision raise the difficulty in training the coefficient estimation branch from scratch. We thus performed pre-training to handle this issue, where we generated linear and non-linear sRGB image pairs as training data. The pre-training encourages the network to learn an initial mapping between linear to nonlinear sRGB images, which was effective for the convergence of subsequent training. The “Expert C” subset of the Adobe FiveK dataset [82] was used to train the aesthetic network. We modified the input images to the same exposure levels as the retouched ones to avoid biased learning due to exposure differences. After that, we fixed the aesthetic network and trained only the coefficient estimation branch. For this finetuning, training images were chosen from the clean raw subset (obtained in burst mode) of the HDR+ dataset [29]. We used the exact input resolution of 256 × 256 in both the pre-training and the fine-tuning to avoid image resizing. For the joint operation branch, we selected the “Outdoor” subset of the RAISE dataset [80] as the training set. To generate degraded images, the original raw images were first darkened by random scale factors in the range of 1-16, which simulates exposure compensation of up to 4 stops, then cropped to 64 × 64 and mixed with the synthetic noise.

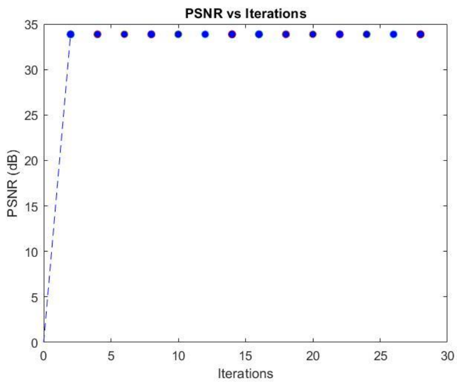


Fig. 5. Illumination adjustment results of iterations vs PSNR.

The proposed system was implemented in Matlab R2021a and trained with several processing toolboxes. The suggested framework carries out three operations: light adjustment, colour improvement, and denoising. We ran three trials to determine the ideal setup for these procedures. We started by looking at how well the illumination adjustment worked. The results analysis provides insights into the effectiveness of the proposed progressive joint low-light enhancement and noise removal algorithm. Here's an explanation of the key findings:

1. Difference in R (Red) and L (Luminance) Channels:

The reported differences in the R and L channels indicate the changes made during the enhancement process. These values represent the magnitude of alterations in the color and brightness aspects of the image. The decreasing values across iterations suggest that the algorithm progressively approaches convergence, indicating refinement in the enhanced image.

2. SSIM (Structural Similarity Index):

The SSIM value of 0.9817 indicates a high degree of similarity between the enhanced image and the original image. A value closer to 1 suggests strong structural similarity, implying that the enhancement preserves the essential structural characteristics of the original image.

3. PSNR (Peak Signal-to-Noise Ratio):

The PSNR value of 33.8689 dB indicates the quality of the enhanced image in terms of signal fidelity and noise suppression. A higher PSNR value suggests lower noise levels and better preservation of image details compared to the original image.

4. NIQE (Natural Image Quality Evaluator):

The NIQE value of 4.6847 provides an assessment of the naturalness and quality of the enhanced image. Lower NIQE values indicate higher image quality, suggesting that the enhancement process has effectively improved the perceptual quality of the image.

5. Mean and Standard Deviation Comparison:

The mean and standard deviation values of the enhanced and original images are very close, indicating that the enhancement process has not significantly altered the overall brightness and contrast characteristics of the image.

Overall, the results analysis indicates that the proposed algorithm successfully enhances the low-light image by effectively reducing noise, improving structural similarity, and enhancing perceptual quality while preserving essential image characteristics such as mean intensity and standard deviation.

diff_R: 12.7483	diff_L: 0.021002
diff_R: 0.0014135	diff_L: 0.00027117
diff_R: 0.00050829	diff_L: 8.1514e-05

SSIM: 0.9817
PSNR: 33.8689 dB
NIQE: 4.6847
Enhanced Image:
Mean: 0.2972
Standard Deviation: 0.2299
Original Image:
Mean: 0.2971
Standard Deviation: 0.2313

5. CONCLUSION

In this research, we introduced a learning-based approach for improving low-light images. Unlike previous research, the proposed system conducts joint illumination enhancement, colour enhancement, and model-specific denoising sequentially. To make this approach more feasible in real-world applications, we created a two-branch structure that handles coefficient estimation, joint augmentation, and denoising across domains. This approach allows it to be retrained for a new camera model with only a few new image samples, dramatically decreasing the human work necessary to collect huge amounts of paired data. Furthermore, the collaborative process enables the network to be more durable and lightweight while maintaining performance. Extensive testing demonstrated that our system surpasses existing cutting-edge algorithms and successfully improves the quality of low-light photos. Our future research.

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