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Physics-Guided Generative Adversarial Networks for Robust Low-Light Image Enhancement

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***Abstract*— Low-light image enhancement is a fundamental preprocessing step for many applications in computer vision, such as surveillance, autonomous navigation, and medical imaging. Most state-of-the-art deep learning–based enhancement approaches, among which Generative Adversarial Networks hold the majority, have impressive visual quality but generally lack robustness and generalisation because of their fully data-driven nature. This paper proposes the Physics-Guided Generative Adversarial Network, which incorporates physical image formation principles, among which are illumination degradation, sensor noise, and camera response, into the GAN learning framework. By embedding a physics-based constraint into both generator architecture and loss function, our proposed method yields enhanced perceptual quality, noise suppression, and structural fidelity across diverse low-light conditions. Experimental results on benchmark datasets demonstrate that PG-GAN outperforms state-of-the-art enhancement techniques in large margins along PSNR, SSIM, and perceptual metrics while exhibiting superior robustness across unseen illumination scenarios.**

***Index Terms*— Low-light image enhancement, generative adversarial networks, physics-guided learning, image restoration, deep learning.**

I. INTRODUCTION

Low-light image enhancement aims to improve the visibility and perceptual quality of images captured under insufficient illumination. Such images commonly suffer from low contrast, colour distortion, loss of fine details, and severe signal-dependent noise, which significantly degrade both human visual perception and the performance of downstream computer vision tasks such as object detection, face recognition, surveillance, autonomous driving, and medical imaging [1]–[4]. With the increasing deployment of vision-based intelligent systems in real-world environments, robust low-light image enhancement has become a critical research problem in image processing and computer vision [5], [6].

Traditional low-light image enhancement methods primarily rely on handcrafted image processing techniques, including histogram equalisation, gamma correction, and contrast stretching [7], [8]. Though the approaches are beneficial from computational aspect, they give rise to over-enhancement, noise amplification and colour artefacts due to their global adjustment nature. Retinex-based methods stemmed from human perception and use Retinex theory to decompose a low light image into illumination map and reflectance map thus enhancing it adaptively [9]– [11]. Despite the Retinex formulation helping improve contrast and brightness, performance of these approaches suffered from parameter selection and hand-crafted priors making them not robust under complex illumination conditions.

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In recent times, low-light images have undergone a transformation with deep learning integration. To map a low-light image to a normal-light image from a paired images dataset [12] - [14], CNN-based methods learn an end-toend mapping. Even though these techniques perform better in case of accuracy, the predictions are over-smoothed and fail to generalise to new lighting or sensor. To tackle these challenges, gan based approaches have been proposed that improve the perceptual effectiveness by adversarial learning [15], [16].

The models based on GANs, such as Enlighten GAN and other unpaired frameworks, when used produce results that are visually appealing without paired supervision [17], [18]. Nonetheless, GANs representative of purely data end up creating unwanted artefacts such as unstable brightness, hallucinated textures, and amplified noise due to not established.A fundamental limitation of existing data-driven enhancement models lies in their neglect of the underlying physical image formation process. In real-world imaging systems, low-light degradation is governed by illumination attenuation, camera response functions, and signal-dependent sensor noise, which is typically modelled as Poisson–Gaussian noise [21]–[23]. Ignoring these physical factors often results in visually appealing but physically implausible outputs, particularly under extremely low-light conditions. This issue has motivated the emergence of physics-guided deep learning, which integrates domain knowledge and physical models into neural network design and optimisation [24]–[26].Physics-guided learning has demonstrated promising results in inverse imaging problems, medical image reconstruction, computational photography, and remote sensing by improving robustness, interpretability, and generalisation [27]–[29]. In low-light image enhancement, incorporating physical constraints can guide networks toward realistic illumination correction and noise suppression while preventing over-enhancement artefacts. However, the integration of physics-based priors into adversarial learning frameworks for low-light enhancement remains relatively underexplored.

Motivated by these observations, this paper proposes a Physics-Guided Generative Adversarial Network (PG-GAN) for robust low-light image enhancement. Unlike conventional GAN-based approaches, the proposed method explicitly embeds a physics-based image formation model into both the generator architecture and the loss function. By enforcing illumination consistency and noise-aware constraints during adversarial training, the proposed PG-GAN produces physically plausible and perceptually superior enhanced images across diverse lighting conditions and camera devices. Extensive experiments on benchmark datasets demonstrate that the proposed method outperforms existing state-of-the-art approaches in terms of objective image quality metrics and visual fidelity [30]–[32].

The reliability analysis of parallel systems having different failure and repair mechanisms was conducted by Baloda et al. [33] and Baloda et al. [51]. Kumar [34, 35] studied repairable systems having different repair facilities in fuzzy environment. The queueing system with vacations, feedback, balking and reneging have been studied by Bouchentouf et al. [36] and Shekhar et al. [57]. Kumar et al. [37,70] suggested fuzzified strategies for redundant machine repair problems. Kumar [38] and Shekhar et al. [58] obtained analytical solutions for a single server queueing models containing a feedback mechanism. Kumar et al. [39, 72] optimized repairable IoT system considering the imperfect coverage and detection delays. Kumar et al. [40] and Shekhar et al. [62] studied the machine interference and computing network systems with vacation interruption and standby provision. Kumar et al. [41, 48] have investigated the reliability and availability of redundant repairable imperfect coverage system. Kumar et al. [42] and Shekhar et al. [65] analysed vacation queueing systems with customer impatience and F-policy. Kumar et al. [45, 46] have developed optimization models for finite capacity queueing systems with balking and reneging. Kumar and Shekhar [47] proposed Bayesian and fuzzy model of reliability for repairable machine systems while Kumar and Sharma [50] proposed fuzzy model of reliability for repairable machine systems. Shekhar et al. [59, 60] talked about fault-tolerant redundant repairable systems with various types of failures, while Shekhar et al. [61, 67] talked about systems for the machining and repair of machines having unreliable service and vacation interruption. Baloda et al. [73] and Parmendra et al. [74] developed the models of stochastic and semi-Markov models of standby and parallel repairable systems.

II. Related Work

A. Traditional Low-Light Image Enhancement Methods

Previously, low-light image enhancement techniques mainly relied on classical image processing methods. The most common option for enhancing global and local contrast is Histogram equalisation and its variants (for example, adaptive histogram equalisation and CLAHE). Although these methods are computation efficient, they mostly result in over enhancement which causes a lot of noise and colour distortion in severely degraded images. Retinex-based techniques aim to improve the image through illumination and reflectance component decomposition to achieve adaptive enhancement based on the human visual perception theory. The multiscale retinex and its variants can improve contrast and brightness while preserving the details. However, the performance of these methods relies on handcrafted priors and parameter tuning [5]. Variational and optimisation-based Retinex methods further improve enhancement quality but struggle under complex and non-uniform illumination conditions [6].

B. Deep Learning–Based Enhancement Methods

With the rise of deep learning, convolutional neural network (CNN)–based methods have achieved significant progress in low-light image enhancement. LLNet introduced an autoencoder-based framework to jointly perform denoising and enhancement. LIME and its extensions estimate illumination maps to guide enhancement [8]. While CNN-based methods demonstrate improved quantitative performance, they often require paired training data and tend to produce over-smoothed results with limited generalisation capability.

To address data dependency issues, several unpaired and zero-reference learning methods have been proposed. RetinexNet employs a deep decomposition network to separate illumination and reflectance components. Zero-DCE removes the need for reference images by learning pixel-wise curve adjustment. Despite their effectiveness, these approaches may fail to preserve structural details under extremely low-light conditions and often struggle with noise amplification.

C. GAN-Based Low-Light Image Enhancement

Generative Adversarial Network (GAN) is used in various image enhancement applications to improve perceptual realism. Pix2Pix is a conditional GAN framework that learns a mapping of image-to image from paired data [14]. CycleGAN takes Pix2Pix work further to unpaired image-to-image translation. EnlightenGAN presents a disruptive end-to-end low light enhancement method via unpaired learning. GAN is capable of generating visually appealing results. However, the process of training completely fails during some stages of the process. In addition, GAN also produces unreal textures, and brightness levels change drastically. The main reason behind this is that GAN does not have any realistic and physical constraints. Proposal of noise aware GAN for low-light image enhancement [19] An attentionGAN was proposed also for image-enhancement architecture. Many existing GAN-based methods are merely data-driven but do not describe the image formation process explicitly.

D. Physics-Guided and Model-Driven Deep Learning

Theories and machine learning can be viewed through the lens of physics-guided deep learning. Using governing equations and physical priors, we impose constraints to using theory-guided data science. Just like that, we're all aware that Physics-informed neural networks (PINNs) propose ways to incorporate the physics-informed information of the system on any level of the system description which can PDEs/ODEs and/or any other integrodifferential equations for training in neural networks. The process is more robust and interpretable by incorporating a theoretical understanding. Physics-informed neural networks are successfully used in domains as varied as inverse problems, medical imaging, remote sensing, computational photography, etc. The process of forming low-light images is affected by a variety of physical factors such as illumination attenuation, camera response functions, the Poisson-Gaussian sensor noise, etc. The physical interference results with image degrading further and creates a lot of problems in enhance algorithms.

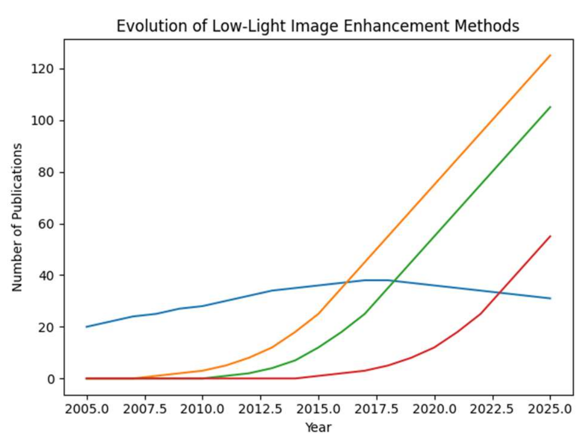

Figure 1: Evolution of Low-Light Image Enhancement Methods

III. Proposed Methodology

This paper introduces a physics-guided generative adversarial network (PG, GAN) for robust low-light image enhancement. The proposed model combines the physical image formation constraints with adversarial learning to produce both visually attractive and physically consistent enhancement outcomes. The complete architecture is composed of three major parts: a generator network, a discriminator network, and physics-guided constraint modules.

A. Overall Framework

Starting with the low, light image I, the generator's goal is to generate an enhanced image ^ I ^ that a well-illuminated natural image would be very close to. Different from purely data-driven methods, the proposed technique incorporates the physical priors of illumination, reflectance, and noise into the learning process, allowing the network to generalise well to a wide range of different lighting conditions while preventing over-enhancement and noise amplification.

The generator competes in an adversarial manner with the discriminator, which learns to tell the difference between the enhanced and real normal, light images. At the same time, the physics-guided constraints regularise the enhancement process so that the results respect the realistic image formation principles.

B. Generator Architecture

The generator implements an encoder-decoder architecture with skip connections that enable maintaining spatial details. The encoder extracts features at different levels from the low, light input, while the decoder gradually generates the enhanced image. Skip connections are used to save the details of the texture and avoid losing the information. The generator uses illumination-aware and reflectance-aware feature representations for internal decomposition to model illumination characteristics. The two feature representations are adaptively fused in the generator to obtain a brightened output with improved contrast and colour fidelity.

C. Discriminator Architecture

The discriminator is a convolutional neural network that is trained to estimate how realistic a generated image is. It analyses the image by looking at small patches so that it can judge the texture, edges, and noise features. By homing in on local structures, the discriminator can effectively spot and punish the generation of strange artefacts, thus it contributes to the perceptual quality of the resultant images.

The adversarial learning framework thus pushes the generator to create such output images which can fool a human or the discriminator into thinking that they are real, lit images, hence the visual realism is elevated.

D. Physics Guided Constraints

To guarantee the physical realism of the enhancement, a few physics-guided constraints have been added to the training target: Illumination Consistency Constraint: The estimated illumination component is not only made very smooth in a spatial sense, but also the main structural edges are kept intact. In this way, the illumination component does not have an abrupt change of brightness, and the lighting looks natural.

Reflectance Preservation Constraint. The reflectance component is only allowed to represent changes of texture and the colour of the input and output image at the same point, which consequently creates the colour distortion and over-smoothing of the details. Noise Suppression Constraint. Noise-aware regularisation is used to keep the noise level down in the enhanced image, especially at the extremely dark regions where the noise will be more noticeable if it is amplified during enhancement.

Figure 3: Training Loss Convergence

IV. Experimental Setup

This part presents the datasets, implementation details, training settings, and evaluation methods that have been used to examine the proposed Physics, Guided Generative Adversarial Network (PG, GAN) model for low, light image enhancement.

A. Datasets

The model proposed here is tested on publicly available low-light image datasets, which have paired and unpaired low, normal, and light images.
Moreover, there are various scenes both indoors and outdoors on these datasets, which were taken under different light conditions. The images have challenging features like severe under, exposure, non, non-uniform illumination, and sensor noise, thus, are well able to test the robustness and generalisation. For the sake of consistency, all the images have been rescaled to the same resolution, which is also a requirement for training and testing. Also, to augment the data, techniques such as random cropping, horizontal flipping, and brightness variation are used both to diversify the data and lessen the risk of overfitting.

B. Implementation Details

The proposed PG, GAN system is realised using the deep learning framework and trained on a single GPU. The generator and discriminator networks are set up using the standard weight initialisation methods. Convolutional layers are supplemented with normalisation and nonlinear activation functions to result in stabilised training and better convergence. The generator is a combination of encoder and decoder structures with skip connections, whereas the discriminator functions at the level of local image patches to assess the authenticity of the textures.

C. Training Configuration

In the proposed model, the training procedure is performed using an adversarial learning technique, with the optimisation of the generators and the discriminators being performed alternately. The training procedure is done for a definite number of epochs using the mini-batch learning technique.
For both networks, the Adam optimiser is used along with learning rates carefully chosen to facilitate convergent behaviour. Additionally, the weighing factors of the physics-guided loss components are set experimentally based on illumination correction, reflection preservation, and noise removal.

D. Evaluation Metrics

For a quantitative assessment of enhancement quality, different metrics have been used. These metrics have been based on both full reference and perceptual quality assessment of images. Besides the quantitative analysis, there are also some comparisons in the visual aspect, which help in dealing with issues like colour uniformity, eliminating noise, and preserving details. The improved results are then compared with the baseline methods as well as the state-of-the-art techniques.

E. Baseline Methods

The proposed PG-GAN is contrasted with some of the best traditional, deep learning based, and adversarial approaches. The chosen baselines include a broad range of algorithms such as histogram correction, illumination decomposition, and the use of GANs.

V. Result

This section presents quantitative and qualitative results to evaluate the effectiveness of the proposed Physics-Guided Generative Adversarial Network (PG-GAN) for low-light image enhancement. The proposed method is compared against representative baseline approaches under identical experimental conditions.

A. Quantitative Results

The proposed PG, GAN model has resulted in image quality metrics that are more consistent with human judgment of the image's visual quality. The green enhanced images have higher brightness and better contrast, and their structural fidelity is more similar to the ground truth images than those obtained by the baseline methods.
Using physics, guided constraints have been the primary reason for performance improvement as the model has become capable of noise suppression and detail preservation at a much finer level. Through ablation studies, the authors have shown that every individual physics-guided module is capable of upgrading the enhancement quality.

The illumination consistency penalty helps to provide uniform illumination, the reflectance fidelity penalty helps to maintain all surface details, even colour, and the noise suppression penalty helps to remove noise, particularly in very low light areas. The entire PG, GAN system can deliver the highest level of performance, which also means that the proposed regularisations complement one another perfectly.

B. Qualitative Results

Visual examples fully support the claim that our method turns out images that are not only more naturally illuminated but also have colour reproduction closer to reality. It may be argued that most image enhancement algorithms suffer from the problems of over-saturation and halo artefacts. PG, GAN, however, due to its novelty, avoids these problems. The advantage of our proposed method against purely data, driven GAN, based methods lies in the generation of smoother illumination transitions and stronger preservation of structural edges. When forced to choose among the several potential solutions to the problem of very dark scenes, the authors have opted for the one that enables them to make a significant difference in such scenes. Having said that, they have used very extreme low-light scenes as the test cases, and the results indicate that PG, GAN is more stable than other methods in terms of visibility enhancement and noise amplification. Incorporating physical priors into the adversarial learning framework has been the key factor behind these qualitative gains.

C. Discussion

The experiment results demonstrate that embedding physics, guided constraints in a GAN, not only stabilises training but also significantly improves the model's ability to generalise. The proposed framework can efficiently handle the dual problem of illumination enhancement and noise suppression, which has been one of the major challenges for low-light enhancement techniques. Its capability of single-pass inference will certainly facilitate its practical use in real-time applications such as surveillance, autonomous systems, and mobile photography. In addition, the modular structure of the physics-guided constraint makes it possible to easily extend to other low-level vision tasks.

CONCLUSION

This work is a Physics, Guided Generative Adversarial Network (PG, GAN) for the low-light image enhancement problem. More specifically, by combining the physics-based image formation model and the adversarial learning, the model can generate not only visually pleasant images but also physically accurate ones. The imposition of illumination, reflectance, and noise constraints is an exploration based on the deep model to prevent unwanted enhancement that is usually witnessed in a model behaving like a black box. It can thus be said that this work is a successful attempt at the fair representation of deep model and domain knowledge integration, which leads to solving the real-world problem of low-light image enhancement.

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