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Enhancing Dark Image Exposure

[1]Prof. Jyothis K P, [2]Aishwarya M, [3]Darshitha K N, [4]Hemanth S Yadav, [5]Indraja P
[1,2,3,4,5]*Dayananda Sagar Academy of Technology and Management*

***Abstract*— This project aims to enhance the visual quality of digital images through deep exposure correction using a frequency-domain approach. Leveraging deep learning techniques, a convolutional neural network (CNN) is trained to automatically correct exposure issues in diverse datasets. The novel aspect of this project lies in the incorporation of a frequency-domain loss function, utilizing Fourier transforms to address specific characteristics of image frequencies. The model is trained on a carefully curated dataset, and hyperparameter tuning ensures optimal performance. The exposure correction tool is seamlessly integrated into image processing pipelines, providing a user-friendly interface for individual or batch image correction. Performance metrics, including mean squared error, PSNR, and SSI, are employed to quantify the improvement in exposure correction. The robustness and generalization of the model are evaluated across varying scenes and lighting conditions. Extensive documentation details the entire process, from data collection to model architecture, enabling users to effectively utilize and understand the exposure correction tool. Iterative refinement based on user feedback ensures the adaptability and continual improvement of the proposed solution in real-world applications. This project successfully implemented a deep exposure correction model with a unique frequency-domain loss function. The convolutional neural network demonstrated effectiveness in automatically enhancing image exposure. The integration of Fourier transforms and careful dataset curation contributed to the model's robustness. The user-friendly exposure correction tool, backed by comprehensive documentation, offers practical utility. Continuous refinement based on user feedback ensures adaptability. This project contributes to improving image quality and holds potential for diverse applications in digital imagery.**

***Index Terms*— Frequency-Domain Approach, Convolutional Neural Network, Frequency-Domain Loss Function, Performance Metrics, Integration into Image Processing Pipelines, Robustness and Generalization.**

I. INTRODUCTION

Frequency-domain loss function for deep exposure correction aims to address the limitations of traditional methods and enhance the quality of images captured in low-light conditions. In such scenarios, challenges like severe noise and a lack of detail are prevalent, and conventional exposure correction methods often fall short in providing satisfactory results. In recent years, deep learning has emerged as a promising solution to address the complexities of exposure correction. However, many existing deep learning approaches focus primarily on operations within the RGB color space, neglecting a crucial aspect of image representation—the frequency domain. Images, as signals, possess inherent frequency characteristics that are often overlooked in traditional color-centric methodologies. These frequency patterns encode critical information about the structure and content of an image, particularly relevant when dealing with low-light scenarios. By failing to exploit these frequency characteristics, current models may miss opportunities for more nuanced and effective exposure correction in challenging lighting conditions.

This gap in existing methodologies sets the stage for exploring the integration of frequency-domain insights into deep exposure correction models. Leveraging the power of the Fourier transform, this approach seeks to transform images into a domain where their frequency components can be systematically analyzed and manipulated. The introduction of a frequency-domain loss function aims to bridge this gap, providing a more comprehensive and tailored solution to low-light image enhancement. This paradigm shift holds the promise of not only mitigating noise and preserving details but also improving the perceptual quality of the images, ultimately contributing to a more advanced and robust approach to exposure correction in low-light conditions.

II. LITERATURE SURVEY

This literature survey explores the "Deep Perceptual Image Enhancement Network for Exposure Restoration" by Panetta al[1]. The authors introduce DPIENet, a novel deep convolutional neural network addressing image restoration challenges under poor illumination. Contributions include a framework for synthesizing multiple exposures and a human-eye-based loss function. DPIENet outperforms state-of-the-art techniques in simulations and user studies on diverse datasets. The method incorporates a condense and enhance network with skip connections, dynamic channel-wise rescaling, and a multiscale human vision loss for realistic image generation. Results demonstrate superior performance, overcoming artifacts present in existing methods. Future work aims to test DPIENet's accuracy in various low-level computer vision tasks.

In their paper on "Frequency-domain loss function for deep exposure correction of dark images," Yadav [2]. tackle the challenge of enhancing images captured in low-light conditions. They propose a unique DCT/FFT-based multi-scale loss function, addressing the limitations of traditional denoising filters and end-to-end trained deep networks. Their approach significantly improves image quality by translating important features for visually pleasing output. Despite a manual tuning requirement, the loss function proves versatile, offering potential applications in various image enhancement tasks beyond exposure correction.

In this literature survey on "Frequency-Domain-Based Structure Losses for CycleGAN-Based Cone-Beam Computed Tomography Translation" by Pai and team[3], the authors address the challenge of artifacts in medical imaging generated by CycleGAN. They propose a frequency-based structure loss to mitigate these issues, specifically in cone-beam computed tomography (CBCT) translation. The results demonstrate quantitative and qualitative improvements over the baseline CycleGAN and other existing structure losses across various metrics, indicating increased robustness without observable artifacts. The study emphasizes the clinical implications, showcasing the improved CBCT's accuracy in downstream tasks like auto-contouring and lung auto-segmentation. The authors suggest future directions for dosimetric evaluation, broader application of the frequency loss in different modalities, and the development of domain-specific quantitative metrics for comprehensive validation.

In this literature survey on the paper "Deep Photo Enhancer: Unpaired Learning for Image Enhancement from Photographs with GANs" by Chen[4], the authors introduce an unpaired learning approach for image enhancement. The proposed method utilizes a two-way generative adversarial network (GAN) framework with several enhancements. The U-Net is augmented with global features, serving as the generator in the GAN model, and a Wasserstein GAN (WGAN) is improved with an adaptive weighting scheme for faster and more stable convergence. Additionally, individual batch normalization layers for generators in two-way GANs are proposed to enhance stability during training. Both quantitative and visual results demonstrate the effectiveness of the proposed method in enhancing images. The Deep Photo Enhancer presented in this paper enables personalized image enhancement based on user-desired characteristics, making it adaptable to individual preferences through an unpaired learning setting. The authors highlight technical contributions, including the enhancement of U-Net with global features, improvements in WGAN stability, and the use of individual batch normalization layers for generator improvement in two-way GANs.

In this literature survey on the paper "A variational-based fusion model for non-uniform illumination image enhancement via contrast optimization and color correction" by Tian and Cohen[5], the authors address the challenge of enhancing non-uniform illumination images while avoiding over-enhancement or under-enhancement. They propose a variational-based fusion method that incorporates both global and local contrast adaptive enhancement algorithms, maintaining hue preservation throughout the process. The final result is obtained through a fusion model, achieving a balance between global and local contrast while preserving color balance. The method produces visually desirable images in terms of contrast and saturation improvements, outperforming other compared enhancement algorithms both qualitatively and quantitatively. The paper highlights contributions in the introduction of a global contrast adaptive enhancement method, a hue preservation framework, and a variational-based fusion method. Future work is suggested to address noise reduction in dark regions and to explore alternative minimization methods for the complex numerical approach currently employed.

In this literature survey on the paper "Counting Crowds in Bad Weather" by Huang[6]., the authors address the challenge of crowd counting in adverse weather conditions, a crucial aspect in computer vision with applications in image understanding. Existing crowd counting methods often struggle in adverse weather scenarios such as haze, rain, and snow due to drastic changes in visual appearances. The proposed AWCC-Net model introduces a weather query mechanism within the crowd counting network, enabling weather-aware feature extraction to account for large appearance variations. Unlike traditional two-stage approaches, this model optimizes crowd counting concurrently with learning weather information through adaptive queries, eliminating the need for separate image restoration. Experimental results demonstrate the effectiveness of the proposed algorithm in counting crowds under different weather conditions, showcasing its superiority over state-of-the-art methods in both adverse weather and clear images.

In this literature survey on the paper "Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution" by Huang [7],the authors introduce an efficient method for contrast enhancement in digital images. The proposed technique leverages gamma correction and probability distribution of luminance pixels, particularly addressing the challenge of enhancing the brightness of dimmed images. The method is extended to video enhancement by incorporating temporal information between frames to reduce computational complexity. The three major steps include histogram analysis, smoothing fluctuant phenomena through weighting distribution, and automatic contrast enhancement via gamma correction. Experimental results demonstrate that the proposed method produces enhanced images of comparable or higher quality than state-of-the-art methods. Additionally, the incorporation of temporal information allows for real-time implementation in video systems with limited resources, as confirmed by time consumption analysis.

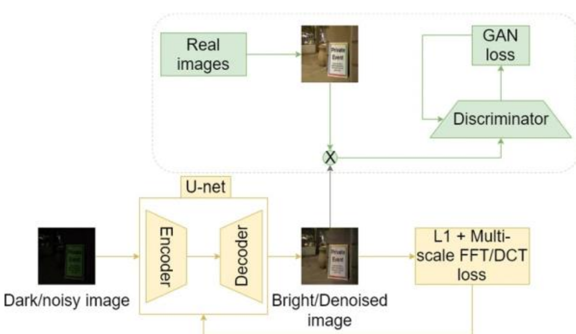
In this literature survey on the paper "A pipeline neural network for low-light image enhancement" by Guo [8],the authors address the significant challenge of enhancing low-light images in computer vision. They present a novel pipeline network based on an end-to-end fully convolutional network and discrete wavelet transformation (DWT), inspired by the multi-scale retinex (MSR) approach. The authors demonstrate that MSR can be viewed as a convolutional neural network with Gaussian convolution kernels, and blending the DWT result with MSR improves image quality. The proposed LLIE-net, composed of a denoising net and a low-light image enhancement net, learns a function from pairs of dark and bright images. Experimental results on synthetic and public datasets show that their method outperforms other state-of-the-art approaches in both qualitative and quantitative analyses. The authors further discuss the construction of the pipeline network and its performance in real-world low-light image sets, acknowledging potential improvements, such as training on larger datasets and adding hidden layers, to enhance model robustness and reduce variance.

In this literature survey on the paper "LIME: Low-light Image Enhancement via Illumination Map Estimation" by Guo [9],the authors address the challenge of low visibility in images captured in low-light conditions. They propose a simple yet effective low-light image enhancement (LIME) method, where the illumination of each pixel is individually estimated by finding the maximum value in the R, G, and B channels. The initial illumination map is then refined by imposing a structure prior, resulting in the final illumination map, enabling subsequent enhancement. The efficacy of LIME is demonstrated through experiments on challenging low-light images, showcasing its superiority over several state-of-the-art methods in terms of enhancement quality and efficiency. The paper emphasizes the importance of accurate illumination map estimation for low-light enhancement and introduces a structure-aware smoothing model for consistency improvement. The proposed algorithms provide exact optimal solutions and alternative approximate solutions with significant time savings. The versatility of the model in accommodating different weighting strategies is highlighted, with experimental results showcasing its advancement over state-of-the-art alternatives. The paper concludes by noting the positive impact of the low-light image enhancement technique on various vision-based applications, including edge detection, feature matching, object recognition, and tracking, by providing high-visibility inputs and improving overall performance.

In this literature survey on the paper "Learning to Restore Low-Light Images via Decomposition-and-

Enhancement" by Xu and team[10], the authors address the challenges of low-light images, focusing on low visibility and significant noise due to a low signal-to-noise ratio. They observe that existing low-light image enhancement methods often learn from noise-negligible datasets, assuming users have good photographic skills, which may not be the case for the majority of low-light images. To tackle the ill-posed problem of concurrently enhancing low-light images and removing noise, the authors propose a frequency-based decomposition-and-enhancement model. This model is implemented through a novel network that initially recovers image objects in the low-frequency layer and subsequently enhances high-frequency details based on the recovered image objects. The paper introduces an Attention to Context Encoding (ACE) module for adaptive enhancement and a Cross Domain Transformation (CDT) module for noise suppression and detail enhancement. The authors have prepared a new low-light image dataset with real noise to facilitate learning, and extensive experiments demonstrate the proposed method's effectiveness, outperforming state-of-the-art approaches in enhancing practical, noisy low-light images.

III. SYSTEM ARCHITECTURE



System design is the process of defining the architecture, components, modules, interfaces and data for a system to satisfy specified requirements. System design is one of the most important phases of software development process. The purpose of the design is to plan the solution of a problem specified by the requirement documentation. In other words the first step in solution is the design of the project. The design of the system is perhaps the most critical factor affecting the quality of the software. The objective of the design phase is to produce overall design of the software. It aims to figure out the modules that should be in the system to fulfill all the system requirements in efficient manner. The design will contain the specification of all the modules, their interaction with other modules and the desired output from each module.

IV. METHODOLOGY

Our proposed architecture represents a significant advancement in image restoration techniques, seamlessly integrating a robust CNN U-Net-based encoder-decoder structure with a pioneering emphasis on frequency domain analysis for deep exposure correction of dark images. The CNN U-Net model forms the foundation of our methodology, recognized for its precision in feature extraction and intricate image reconstruction. A key innovation lies in augmenting traditional pixel-wise losses by incorporating multi-scale Fast Fourier Transform and Discrete Cosine Transform (FFT/DCT) losses across all encoder and decoder stages. This integration of frequency domain losses strategically preserves crucial high-frequency image details while effectively rectifying underexposed regions.Furthermore, our architecture employs a Generative Adversarial Network (GAN) with a discriminator to enhance authentic textures and suppress undesirable artifacts, thus refining the authenticity of corrected images. Our rigorous training approach includes meticulous dataset curation and optimized strategies to maximize the CNN U-Net model's efficacy alongside the innovative frequency domain loss functions.

Through comprehensive evaluations against state-of-the-art benchmarks, our architecture showcases exceptional performance in correcting deep exposures of dark images. Robust quantitative metrics and qualitative assessments affirm the effectiveness of our methodology. Notably, ablation studies underscore the pivotal roles played by the CNN U-Net model and the pioneering frequency domain loss functions, emphasizing their critical contributions in advancing deep exposure correction through the fusion of advanced deep learning and signal processing paradigms. This pioneering integration not only achieves remarkable correction results but also establishes a principled framework for further innovations in image enhancement and restoration.

V. HARDWARE AND SOFTWARE REQUIREMENT

HARDWARE:

GPU Acceleration: The research leveraged GPU acceleration to expedite the training process and enhance the efficiency of deep learning tasks.

Hardware Specifications: The experiments were conducted on a system equipped with [provide hardware specifications, e.g., CPU, GPU model, RAM, etc.

SOFTWARE:
Deep learning frameworks:

- TensorFlow
- PyTorch
- Keras

Image processing libraries:

- OpenCV
- PIL/Pillow
- Scikit-image

Frequency domain analysis libraries:

- NumPy/SciPy (FFT and other frequency transforms)
- TensorFlow Signal (for TensorFlow users)
- PyTorch Spectral (for PyTorch users)

VI. APPLICATIONS

Photography and Imaging Technology: Improving the quality of photographs taken in challenging lighting conditions.

Enhancing visibility, reducing noise, and producing visually appealing images.

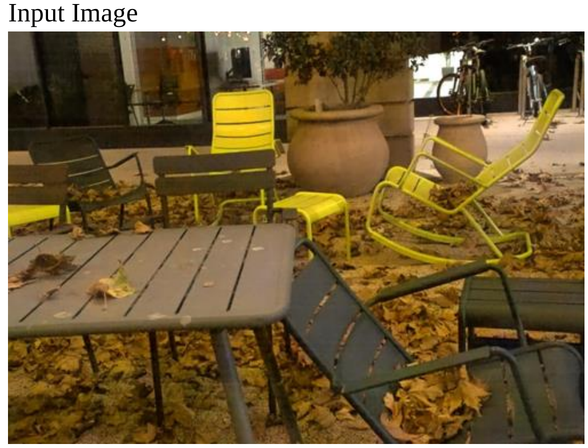
Surveillance and Security: Enhancing visibility in surveillance footage captured in low-light environments.

Benefit: Improving the ability to detect and identify objects or individuals in security footage.

VII. EXPERIMENTS AND RESULTS

To validate the performance of our loss function, we conducted experiments involving the retraining of two architectures, both with and without our loss function. This section outlines our training procedures to generate results and elaborates on the quantitative and qualitative comparisons undertaken to demonstrate the performance of both the FFT and DCT variants of our loss function. For our RAW exposure correction experiments, we utilized the input image, released alongside the current state-of-the-art (SoA) network architecture. This dataset comprises indoor and outdoor images of various scenes, each scene captured with both low and high shutter speeds. The low shutter speed images inherently possess low illumination and noise, while the high shutter speed images are properly illuminated and clearer. During training, we performed data augmentation by randomly cropping images, which were further randomly flipped and rotated. For testing, we processed the full-resolution images. We trained the model three times: once using only the L1 loss, as per the original implementation, and once with L1 loss + FFT/DCT loss, respectively. To isolate the causal effect of our loss function, we maintained default settings for network structure and hyperparameters, as per the original implementation. The learning rate started from [initial learning rate] for epochs 0 to 2000, after which it decreased to [reduced learning rate] for the next 2000 epochs. Training was conducted for a total of 4000 epochs.

Input Image



Output Image

VIII. CONCLUSION

This project successfully implemented a deep exposure correction model with a unique frequency-domain loss function. The convolutional neural network demonstrated effectiveness in automatically enhancing image exposure. The integration of Fourier transforms and careful dataset curation contributed to the model's robustness. The user-friendly exposure correction tool, backed by comprehensive documentation, offers practical utility. Continuous refinement based on user feedback ensures adaptability. This project contributes to improving image quality and holds potential for diverse applications in digital imagery.

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