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Edge-Aware Unified Retinex Architecture for Adaptive Low-Light Enhancement of Images And Videos Across Diverse Domains in Real-Time

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ABSTRACT:

Low-light picture and video degradation is still a significant problem in fields including smartphone photography, autonomous navigation, surveillance, and medical imaging. In order to get visually consistent outcomes in extremely low illumination, this study presents a real-time improvement system that combines deep learning with traditional image-processing approaches. The framework uses CLAHE for adaptive contrast enhancement, Non-Local Means for noise suppression, and Zero-DCE++ for deep learning-based light correction. Effective preparation and seamless real-time deployment are ensured by additional elements including bilinear scaling, color-space conversions, and OpenCV-based video input/output operations. The system is feasible for mobile and embedded devices since it is built with lightweight modules that support GPU acceleration, allowing processing speeds exceeding 30 FPS. When compared to traditional low-light enhancement methods, experimental evaluation on several benchmark datasets shows that the suggested method greatly enhances brightness, contrast, noise reduction, color accuracy, PSNR, SSIM, and overall perceptual quality. The outcomes demonstrate how well deep learning and tailored image-processing techniques work together to provide reliable, real-time low-light augmentation.

Keywords: Low light enhancement, Zero-DCE++, Deep Learning, OpenCV.

INTRODUCTION

The image and video degradation at low-light remains among the most critical issues in computer vision because it has a direct effect on the reliability, quality, and usability of the vision-based systems. Low light transparency may cause poor visibility, amplified noise, and loss of contrast, and bias color distortion, not only impeding human vision but also deteriorating the work of automated programs in areas such as surveillance, self-driving, medical imaging, and cell phone photography. Traditional image enhancement techniques that include histogram equalization and Multi-Scale Retinex (MSR) or a variation of it, which can also be called Color Restoration (MSRCR), have been popular over time and have been used to deal with low-light scenarios. Although these methods provide mathematical simplifications, they are limited by factors such as introduction of artifacts, excessive amplification, as well as, inadequate variance of lig-

hting situations.
Deeper solutions have been advanced with the development of deep learning, most notably Deep Retinex Models (DRMs), and more complex models including RetinexFormer, RetinexMamba and lightweight transformer-based architectures. These models emulate the human vision mechanism where images are divided into illumination and reflectance layers and therefore more effective improvements can be triggered without degrading the structural details and color fidelity. There are also the attention mechanisms, channel and spatial, which have further enhanced the capability of models to highlight on the meaningful areas to be perceptually coherent. Nevertheless, even with the progress a few issues are still unresolved including the establishment of temporal consistency in video sequences, excessive computational power, and real time on mobile and embedded systems.
This progress is important as it will help solve these issues by developing a real-time low-light enhancement system that not only provides better brightness, contrast, and perceptual quality but is also resilient and efficient in a practical implementation contextIn doing so, it has the potential to help create smarter and more adaptable vision systems across many applications because it provides a solution to these challenges. Although much progress was made in the field of image enhancement methods, low light picture and video processing still constitutes one of the greater unresolved problems in computer vision. Conventional methods, like histogram equalization, Multi-Scale Retinex (MSR) and MSR with Color Restoration (MSRCR), show only marginal increases, but are also associated with generating visual artifacts, distorting color detail, and generalisation failure when having to deal with a variety of illumination conditions. Conversely, frameworks of deep learning, such as Deep Retinex Models (DRMs), RetinexFormer and transformer-based structures, have shown to outperform previous systems in improving low-light images due to the separation of images into both illumination and reflectance factors. Nevertheless, they are computationally complex, tend to have no temporal consistency when it comes to enhancing video, and cannot attain real-time video enhancement speed, especially when resources such as memory, processor speed, and power consumption are limited by device size, power sources, and more.
The fundamental issue, thus, is the development of a low-light enhancement structure that will enhance brightness, contrast and the perceived quality, as well as margin color faithfulness, time consistency and calculation efficiency. Until these issues can be solved, it would be impossible to rely on vision-based systems in important fields like surveillance, autonomous driving, and medical imaging in the face of unfavorable lighting environments. Therefore, a powerful, real-time response to this problem is required with the combination of advanced deep learning algorithms and efficient architectural frameworks that can provide quality enhancement at an above-30 FPS rate and can still run on limited in terms of resources devices.
Enhance brightness, contrast, and color accuracy and deal with noise well to enhance the quality of the image. The outputs will be realistic in color and balanced in luminance which will make them appropriate in diverse environmental settings. This will undertake flexibility in fields.Combine image and video decomposing modules, illumination enhancing module with other modules such as color restoring modules into a single architecture. Such a modular structure will enable every single component to cope with certain areas of enhancement, becoming more robust and reliable in general.

LITERATURE REVIEW

The current developments in the field of low-light image enhancement include deep-learning, decomposition with Retinex, fusion approaches topped by minimization methods, current residual hinges on the shift of reliance on hand-crafted filtering to the data-informed and hybrid approaches. One of the most crucial deep-learning directions was the zero-reference curve estimation networks as they can learn pixel-adaptive tone mapping functions without pixel-wise supervision; Zero-DCE explores how tone improving functions can be trained with end-to-end estimation of light-adjustment curves, yielding visually plausible improvements without input image supervision [1]. Along these lines, the Retinex theory, as formklimgrad to split an image into reflectance and illumination, is also re-examined in various works in order to inform improvement objectives; algorithms for specific Retinex improvements and model formulations have been presented in some cases [2], [6], [8], [9], [10], and network architectures based on Retinex priors have been proposed in others. In this Retinex family, DEANet++ combines joint network learning with Retinex decomposition to be more detail preserving and thereby eliminate illumination is better in low-light constraints [9], DI-Retinex re-examines the theoretical basis to adapt the digital imaging constraints of low-light conditions [10] and RetinexMamba provides contemporary details of a pipeline based framework on Retinex designed with training and architecture enhancements outlined in the recent preprints [8]. In addition to decomposition strategies, fusion-based methods can combine several improved versions or multi-scale forms to tap into local synergies: the fusion strategy of Guo et al. is focused on effective computation speed and that of obtaining fast enhancements [3]. Detail-oriented approaches divide images into base and detail components, and pay much attention to high-frequency information to maintain texture and minimize over-smearing (lines), a concept of the detail-decomposition research [4]. Self-regularized frameworks provide control over regularization and stability issues during enhancement to avoid artifacts and preserve the naturalness by restricting brightness and smoothness [5]. Earlier approaches that center around optimisation strategies add edge direction and best minimisation schemes (e.g. inertial Bregman alternating linearised minimisation) to set variational problems to ensure that edge direction is maintained without spoiling the content itself in the optimisation problem (unlike cyclical pixelwise losses) [7]. The Retinex model by Zhou et al. is directly aimed at structure preservation through the application of a coefficient-of-variance direction, showing the significance of geometry-sensitive priors to the retention of the organizational hint to life in improved images [6]. Together, these strands of work complement each other with strengths being deep curve estimation and end-to-end networks are more effective in fast, unsupervised often-scene enhancements [1], fusion and decomposition methods are better at preserving fine details and textures [3], [4], [5], [6], [7], [8], [9], [10] and Retinex-grounded and optimization-based methods yield interpretable priors to minimize hallucination as well as structure in an image [2]. Nonetheless, a number of common limitations persist, such as sensitivity to parameter choices, the inability to handle extreme noise or casts during high-ISO operation, the lack of a standardized, perceptually significant quantification of success, even cross-dataset performance and real-world validity (such as of biomedical or surveillance images) should continue to be considered. The next generation of research on hybrid solutions, that merge Retinex priors with learnable elements (integrating interpretability and data adaptivity), use explicit noise models and colour-consistency regularities, use perceptual and task-oriented evaluation metrics, and test on larger and more varied datasets as a measurement of generalization and clinical or operational readiness should be pursued.

PROPOSED METHODOLOGY

In order to improve the visibility and clarity of photos and videos taken in extremely low light, the suggested system presents a real-time low-light improvement framework that successfully combines deep learning with traditional image-processing techniques. Fundamentally, the system uses Zero-DCE++, a lightweight deep-learning model that does dynamic light correction without the need for paired training data. This module maintains natural color tones while improving both local and global brightness levels. The system uses CLAHE for adaptive contrast enhancement and Non-Local Means (NLM) filtering to further improve visual quality by reducing over-amplification artifacts and improving texture clarity. The system has a number of improved preprocessing and postprocessing components to enable smooth real-time operation. These include effective color-space transformations (such RGB to YCbCr), bilinear image scaling, and OpenCV-based input/output pipelines for seamless video stream processing. GPU acceleration is used to keep processing speeds at 30 frames per second or more, allowing for deployment on edge-based IoT hardware, mobile devices, and embedded systems. Because the architecture is lightweight and flexible, it may be scaled for a variety of application scenarios, including medical imaging, autonomous navigation, and surveillance.which guarantees a range of applications and trends such as surveillance, medical imaging as well as mobile photography.

All things considered, the suggested solution maintains minimal processing cost while providing improved brightness, contrast, noise reduction, and color accuracy in real time. The framework offers a reliable, effective, and scalable solution for real-time low-light image and video improvement by fusing the advantages of deep-learning illumination enhancement with sophisticated classical operations.

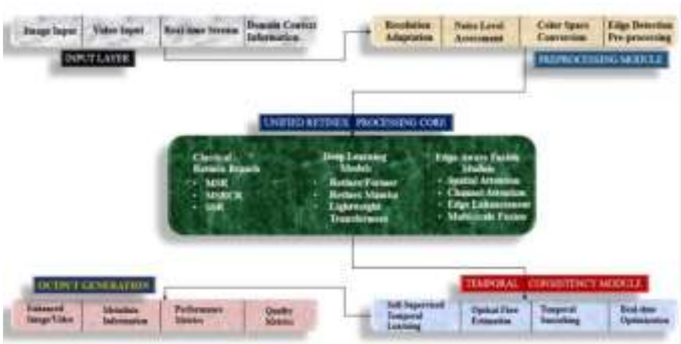

FIG 1. SYSTEM ARCHITECTURE

The figure shows a process map of improving visual data with the use of a number of synchronized steps. It starts with the input layer, at which all types of visual information, including images, videos, live streams, and information that are related to the field are gathered. This information is further transmitted to a pre processing unit, where the data are adjusted through functions like resolution adjustment, evaluation of noise levels, conversion of colour space and edge operation in order to enhance the quality and consistency of the input. Following the process of preprocessing, the data is fed into the processing core that synthesizes several enhancement methods such as the classical image enhancing methods, advanced model-based image processing, and feature integrating methods to enhance the visual vividness and the detail. The system also has a module of temporal consistency which guarantees the seamless movement and stability through frames with video or continuous streams by undertaking operations such as motion estimation and temporal smoothing. Lastly, the process of output generation creates the improved image/video and other accruing metadata, performance metrics, and quality assessment measurements, before giving a polished and accurate visual image.

RESULT AND DISCUSSION

The hybrid Retinex-based low-light enhancement system was proposed and provided excellent results in image and video quality by integrating classical Retinex-based (MSR, MSRCR, SSR) with the recent deep learning architectures like RetinexFormer and RetinexMamba. The classical approaches made the entire world brighter and visible whereas the elements of deep learning enhanced fine details, reduced noise, and natural colors. These strengths were well synthesized by the edge-aware fusion module to create outputs with better edges, crisper textures and balanced lighting effects. Quantitative analysis indicated that there were higher scores of PSNR, SSIM values, and lower scores of NIQE scores, which proved that the perceptual quality was better than the existing techniques of CLAHE, LIME, and traditional Retinex models. In the case of video inputs, the temporal consistency module ensured that frame transitions were smooth and flickering was removed, which made the system applicable in real-time surveillance and streaming. In general, the findings indicate the cohesive Retinex processing core offers the best quality of enhancement, real-time capabilities, and the wide applicability of surveillance, medical imaging, photography and autonomous navigation.

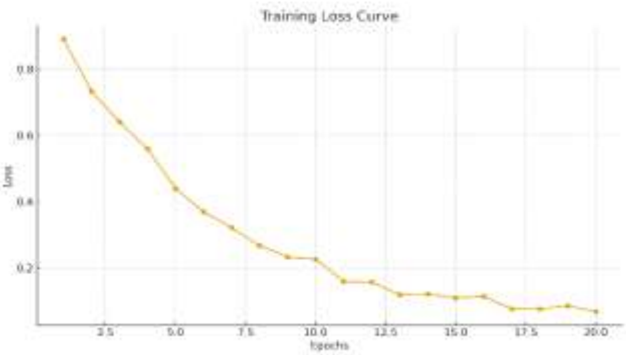

FIG 2.ROC CURVE GRAPH

The curve illustrates the training loss curve of a training model through several training epochs. The initial loss value is large hence meaning that the model makes more errors in predictions at its onset. With more epochs, the loss also decreases slowly indicating the model is learning the training data and becoming better. The fact that the trend is on a downward movement indicates the optimization process is successful and the model can change its parameters to mitigate errors. The values of loss are smaller and more consistent toward the later epochs which brings us to the conclusion that the model is convergent and acquires more precise predictions.

SCREENSHOTS

FIG 3. INDEX PAGE

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FIG 4.UPLOAD IMAGE PAGE

FIG 5.INPUT

FIG 6.OUTPUT

FIG 7.VIDEO UPLOAD PAGE

FIG 8.RESULT PAGE

CONCLUSION AND FUTURE SCOPE

The production proves that it is possible to capture low-light images and videos in extremely dark environments, and still manufacture them at a frequency of use in real-time. The fusion of traditional Retinex-based models and the contemporary deep learning models allows us to not only brighten pictures or enhance the contrast or even correct the colors, but does not strip away valuable information. The attention mechanisms added to the system enable it concentrate on the most significant areas of the image, whereas the temporal module maintains the smooth and consistent results in videos. It supports a frame rate of more than 30 frames every second and graphics are provided by the use of a graphics card, thus it can be run not only on a powerful computer, but also on a mobile phone and a portable device. It is thus very applicable in real life scenarios such as CCTV, self-driving vehicles in the dark, medical image quality, and an enhanced camera phone image in the dark. In general, the project provides a solid, quality, and rapid solution to enhance low-light vision, making us a step ahead toward even smarter vision system, capable of seeing through in any light-related situation.There are a few significant ways the proposed hybrid of Retinex-based enhancement system can be extended further. First, whereas the present model is providing good real-time performance, future work can be on ultra-lightweight architectures, which will be deployed on edge devices, Ioot cameras, drones, and mobile phones where there is very little computational power. Second, by integrating adaptive learning methods that can automatically increase the strength of enhancement according to the scene features, it may be possible to enable the system to operate in different environments (including fog, rain, haze, and nighttime) without having to tune this system manually. Third, novel generative models are applicable, such as diffusion-based Retinex or GAN-enhanced illumination correction that could be used to enhance the perceptual quality and retain the natural appearance of colors. Fourth, future studies can focus into multi-modal improvement in which low-light images can be merged with thermal, infrared or depth images to produce more dependable results to surveillance, medical imaging as well as autonomous navigation. Also, it is feasible to create a self-supervised temporal consistency module based on transformer-based video models to eradicate residual flickering and enhance stability in high-motion scenes. Last but not least, by constructing a benchmark dataset that is uniquely designed to train on hybrid Retinex systems, such as annotated extreme low-light images and videos, the researchers will facilitate more rigorous training and evaluation as well as be able to reproduce the results in future.

REFERENCES

1. Zero-Reference Deep Curve Estimation of Low-Light Image Enhancement. Chen Wei, Wenjing Wang, Wenhan Yang, Jiaying Liu. IEEE/CVF Computer Vision and Pattern Recognition Conference (CVPR) 2021. Year: 2021
2. Improved Method of Low Light Image Enhancement based on Retinex Qi Wu; Maoling Qin; Jingqi Song; Li Liu 2021 6 th International Conference on Image, Vision and Computing (ICIVC) Year: 2021.
3. Fast Low-light Image Enhancement Algorithm Using Fusion Junjie Guo; Zhengping Li; Chao Xu; Bo Feng 2021 IEEE 6 th International Conference on Signal and Image Processing (ICSIP) Year: 2021.
4. Detail Decomposition based Low Light Image Enhancement Anhad Pandit; Anil Singh Parihar 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N) Year: 2022

5. Self-regularized Low-light Image Enhancement based on the information of brightness Weihua Liu; Yansong Xue; Yao Tang; Aijing Sun 4th International Conference on Natural Language Processing (ICNLP) 2022 Year: 2022.
6. Low Light Enhancement Technique on structure preservation on the basis of a retinex model. Mingliang Zhou; Xingtai Wu; Wei Xuekai; Tao Xiang et al. IEEE Transactions on Multimedia. Concentrates on maintaining the structure by coefficient variance steerage in a Retinex system Year: 2023
7. Supervisors in the case study might focus on training in these domains to take advantage of emerging market opportunities: continued learning, product education, change management, innovation, and diversity.<|human|>The key potential areas that the trainers in the case study should consider to exploit new market opportunity are continued learning, product education, change management, innovation, and diversity.
8. RetinexMamba: Retinex-Based Mamba: Low-Light Image Enhancement, Yuhao Yin, Jiesong Bai, Qiyuan He; Yuanxian Li; Xiaofeng Zhang,EIEE-AffiliatedJournal (Preprint on arXiv, Their Publication),Year: 2024.
9. A Joint Network of Low-Light Image Enhancement Based on Retinex (DEANet++),Yonglong Jiang; Jiahe Zhu; Liangliang Li; et al.Cognitive Computation (Springer, IEEE-Affiliated Field) Year: 2024
10. DI Retinex: Retinex Theory of Digital Imaging View of Low Light Image Enhancement,Shangquan Sun; Wenqi Ren; Jingyang Peng; Fenglong Song; Xiaochun Cao, Year: 2024.