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Enhanced DeblurGAN: An advanced combinatorial model for motion blur removal in low-light photography

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Abstract. This article aims to address the challenge of eliminating low-light motion blur, a problem that lacks effective solutions, despite being crucial in various application scenarios. For instance, it can help in the identification of moving individuals or license plates during nocturnal surveillance, filming running videos after dark, and managing animals in rural areas at night. These examples represent commonplace and significant scenarios. These are all important domains, but few approaches are effective at handling such specific cases simultaneously. This paper utilizes a fusion model to increase the brightness of an image while preserving the photographic details. The motion blur is subsequently eliminated from the brightness-enhanced image. This results in the enhancement of image details and the removal of motion blur. Comparing the model proposed in this paper with the commonly used Deblur model, it becomes apparent that the new model effectively enhances brightness in low-light motion blur while preserving image details and reducing much of the blur. This implies that the model is more versatile, as it can be used not only for images but also for low-light videos.

Keywords: DeblurGAN, GAN, Motion Blur, Low-light.

1. Introduction

Recently, the topic of image deblurring has seen increasing interest among scholars as well as in the business community, primarily due to its vital relevance in specialized fields such as autonomous vehicle operation, and surveillance systems. The traditional deblur model focuses on the blur caused by resolution downgrade. However, low-light motion blur received little attention.

Artificial Intelligence (AI) and Machine Learning. Artificial Intelligence provides algorithms and frameworks for complex tasks, such as image processing and computer vision. Traditional machine learning methods, such as Support Vector Machine (SVM) [1] and Random Forests [2], have been used for image deblurring, but often underperform and lack applicability to complex, real-world data. To solve this issue, Generative Adversarial Networks (GANs) [3] offer a promising solution. GANs have revolutionized the field of image synthesis and manipulation, introducing novel perspectives on solving intricate issues such as image deblurring. GANs [3] have been broadly utilized to recover crisp images from blurred ones, often exhibiting remarkable abilities even with highly challenging and complicated blurs.

The development of Convolutional Neural Networks (CNNs) [4] has revolutionized the field by introducing data-driven methods. Neural network-based deblurring algorithms have produced satisfactory results by learning end-to-end mappings from blurry to sharp images. However, several deep learning models are trained for particular types of blurs and face difficulties in generalizing across different blurring circumstances in the real world.

CycleGANs [5] are utilized for unpaired image-to-image translation and have additionally been adapted for image deblurring. Super-Resolution GANs (SRGANs) [6] are also employed for image deblurring. Targeted for super-resolution tasks but have seen adaptations for deblurring applications,

image deblurring technologies have evolved significantly. Modern machine learning models have overcome these limitations. Initially, methods like Weiner filtering and Lucy-Richardson deconvolution were used to tackle this issue but had limitations in terms of handling various types of blurs effectively. Additionally, the techniques have been extended to night-time image enhancement. Research has specifically addressed challenges associated with nighttime or low-light conditions, such as noise, color imbalance, and loss of detail. However, much of this work is separate from deblurring, and there is a gap in methods that address both challenges simultaneously. This is the problem that this study will try to solve in this paper.

DeblurGAN [7] model functions well on typical motion-blurred images. However, the performance in motion blur situations at night still has significant room for improvement. This field is also crucial to implement, considering the abundance of images and videos shot at night. It remains an essential aspect that cannot be ignored.

To address these limitations, this study implemented a series of refinements to the existing model architecture and adjusted the training parameters. These are the three primary contributions of this article: *(i)*This study introduced a new model structure to expand and improve the application scenarios of the model. Further improved the image detail and resolution generated by the model. *(ii)*Previous models, such as DeblurGAN [2], often perform poorly under certain conditions, such as in low-light or nighttime scenes, where blur can be particularly disruptive. This study addressed this issue by optimizing the training parameters and introducing specialized models and layers capable of better handling these challenging conditions. *(iii)*After rigorous testing and validation, the model shows a significant performance improvement in these specialized scenarios, making it more reliable and practical for real-world applications.

2. Method

2.1. Dataset preparation

2.1.1. GOPRO Dataset. The GoPro [8] dataset is designed to address the issue of image deblurring. The dataset comprises 3,214 high-resolution images, each with dimensions of 1,280 x 720 pixels. It is segmented into 2,103 images for training purposes and 1,111 images designated for testing. Each data point includes a pair of images: one is a high-speed camera capture of a realistically blurred version, and the other is its corresponding sharp ground truth image. The blurry images simulate scenarios where camera shake, or movement might affect image quality in the real world. The GoPro dataset is a benchmark for the development and testing of deblurring algorithms, especially those that employ machine learning techniques.

2.1.2. Microsoft Common Objects in Context (COCO). The Microsoft Common Objects in Context (MS COCO) [9] dataset is an extensive and multipurpose collection of data that caters to multiple computer vision tasks. The dataset includes an extensive collection of 328,000 images and is designed for tasks such as object identification, image segmentation, key-point recognition, and image annotation. These images are varied and encompass everyday scenes and common objects in various contexts. The dataset is valued for its complexity and diversity, providing challenging but fertile ground for developing and evaluating advanced algorithms. It serves as a critical catalyst for expanding the limits of capability within the domain of computer vision.

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2.1.3. Low-Light Dataset (LOL). The Low-Light (LOL) dataset is a collection of 500 image pairs curated for the analysis of managing low-light scenarios. Abbreviations will be explained when first used. As such, this dataset provides researchers and developers with a framework for generating and testing low-light image enhancement techniques. The dataset includes 485 training pairs and 15 testing pairs, covering a range of indoor settings and featuring a resolution of 400 x 600 pixels. The dataset presents a distinct challenge due to the presence of noise inherent to low-light photography. As such, it offers ideal conditions for developing noise reduction and image enhancement algorithms tailored to low-light environments. It is worth noting that the dataset includes naturally occurring noise, without any subjective assessments. One of the unique challenges presented by this dataset is the presence of noise that naturally occurs during low-light photography. Therefore, it is an ideal dataset for developing noise reduction and image enhancement algorithms that are optimized for low-light conditions.

2.2. Enhanced DeblurGAN

In this article, Enhanced DeblurGAN was presented, a new model specifically designed to handle motion blur in dark night scenes. Due to the lack of light, image details are often lost in such scenarios. To address this issue, the pre-trained MIRNet_v2 [10] model was introduced to enhance night images shown in Figure 1, which is employed to process all images before they are input into the generator. Figure 2 illustrates the specific model structure.

Figure 1. Low-light image will be Enhanced before being processed by the DeblurGAN (Photo/Picture credit: Original).

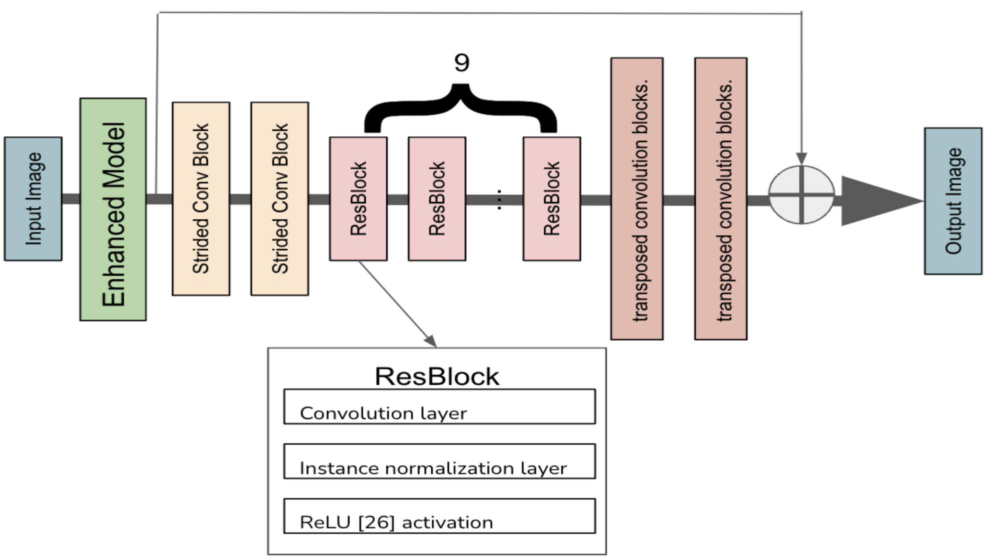

Figure 2. After the picture is input into the first Enhanced Model, it goes through two strided convolution blocks, 9 Resblocks, and 2 Transposed convolution blocks (Photo/Picture credit: Original).

2.3. Implementation details

In the present research, the Adam optimization algorithm was utilized, given its attributes of efficiency and minimal memory consumption, at a specified learning rate. The default settings for Beta 1 and Beta 2 were maintained at 0.9 and 0.999, respectively. The collected dataset consisted of 512 images and they were divided into mini-batches of 16. The model is trained for a total of 500 epochs, each consisting of one forward and one backward pass through the entire dataset. The experiment employs a contemporary GPU to accelerate computation. The training process encompasses an initialization phase for the model parameters and the Adam optimizer, followed by data loading and mini-batch creation. A training iteration is subsequently executed, encompassing the completion of a forward pass for loss computation, a backward pass for gradient determination, and the deployment of an optimization step to update the model's parameters via the Adam optimizer. The model is periodically assessed, and the highest-performing version is saved for future reference. This configuration is intended to provide a dependable and reproducible framework for analysis.

3. Results and discussion

The results clearly demonstrate that the Enhanced Motion Deblur model surpasses the baseline model in restoring fine details in low-light motion blur images. The intricacies in the shadowed regions of the low-light image are easily identifiable after undergoing repair through the Enhanced Motion Deblur algorithm. Further confirming this claim, in Figure 3, the two images on the top left, from left to right, are the original image and the sharpened image. The top right displays the brightened image and the image processed with Enhanced DeblurGAN versions. The bottom two images are partial pictures of the processed image. Comparing the two enlarged pictures below, it is evident that the details in the dark area are more easily observable. It can be observed that the image enhanced by the Enhanced Motion Deblur model is not only brighter but also more detailed. Specifically, the processed image exhibits a notably clearer representation of a patch of grass that is not obstructed by other grass elements.

Despite the improvements, there are challenges with the current method, particularly when facing extreme cases of motion blur. The limitations of the current training data, which is synthetically generated by the model itself, contribute to the shortcomings in restoring these images. This creates an authenticity gap as it may not accurately replicate real-world motion blur situations. In this article, only images sourced from real-world videos featuring actual motion blur have been used, rather than artificially created instances through computational models. Therefore, there is a critical need for a more inclusive and resilient dataset that encompasses the diversity in motion blur found in real-world environments. Looking forward, the objective is to refine the model for improved handling of real-world motion blur scenarios. Additionally, assembling a more expansive dataset of genuine motion blur images and videos is planned to better synchronize the training process with reality.

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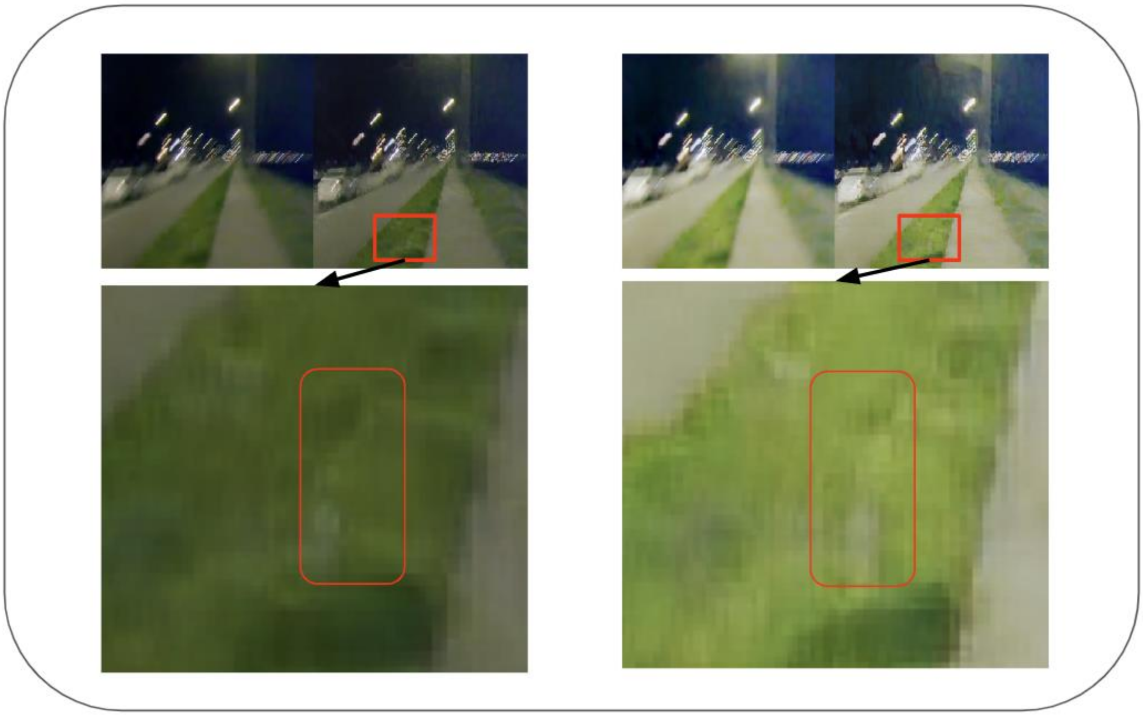

Figure 3. The two images on the top left, from left to right, are the original and sharpened images. The top right displays the brightened image and the image processed with Enhanced DeblurGAN versions. Below are two magnified comparison images of the details (Photo/Picture credit: Original).

4. Conclusion

This study presented the Enhanced DeblurGAN, an innovative combinatorial model designed to mitigate the common issue of motion blur in low-light photography. Unlike the standard DeblurGAN, the Enhanced DeblurGAN model integrates advanced algorithms that handle the complexities of motion blur while producing considerable enhancements in image details and brightness even in challenging lighting conditions. Through extensive experimentation, it is objectively evident that Enhanced DeblurGAN outperforms its predecessor in various low-light scenarios. This is confirmed by quantitative metrics and visual assessment through comparison images. Technical term abbreviations are explained when first used. The model effectively enhances brightness levels while accurately restoring intricate photo details, resulting in superior image quality.

Although the standard version of DeblurGAN has exhibited some efficacy in handling motion blur, our research reveals its limited effectiveness when dealing with severe instances of blurred artifacts. Consequently, our forthcoming academic investigations will be focused on the refinement and enhancement of motion blur removal algorithms to advance the capabilities of the Enhanced DeblurGAN model. Our aim is to push the boundaries of low-light image processing by addressing more intricate forms of motion blur, thus expanding the model's utility in real-world scenarios.

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