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Original Paper

Restoring Image Clarity: Dual-GAN Framework for High-Quality Image Generation from Low-Resolution Blurred Inputs

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ABSTRACT

A key task in computer vision is image restoration, which aims to recover high-quality images from blurry or degraded inputs. In this research, we provide a novel method for restoring high-quality images by combining the advantages of DeblurGAN and ESRGAN (Enhanced Super-Resolution GAN). While ESRGAN focuses on super-resolution and fine detail recovery, DeblurGAN focuses on eliminating blurring artefacts and increasing image details. We take advantage of the complementary strengths of these two architectures and produce a synergistic outcome by combining them in a multi-stage refining process. The suggested method starts by using DeblurGAN to deblur the input photos and improve their clarity and sharpness. Enhance super-resolution GAN is then used to further enhance the deblurred images with a focus on high-frequency detail recovery and super-resolution. The input photos can be fully restored using this multi-stage refinement procedure, which improves visual quality and resolution. Numerous tests show that this method performs better in eliminating blurring artefacts and retrieving fine details. Deblur-GAN and ESRGAN are combined to improve visual quality, resolution, and detail recovery through a multi-stage refinement process. The method effectively addresses the picture restoration issues, showing potential for applications in digital photography, surveillance, and medical imaging.

KEYWORDS

Image restoration, Generative Adversarial Networks (GANs), Deblurring, Super-resolution

1. INTRODUCTION

The skillful use of image restoration techniques to improve the visual quality of photos with low resolution and blurring has attracted a lot of interest in recent years. There are several uses for the capacity to restore crisp, clear features from damaged photos, including medical imaging, surveillance, and the improvement of multimedia content. However, overcoming the difficulties brought on by managing blurring and low resolution at the same time is still an active area of research. This research proposes a novel Dual-GAN (Generative Adversarial Networks) method for image restoration, concentrating on the improvement of low-resolution fuzzy images. The complementary strengths of two GAN architectures, DeblurGAN and ESRGAN, are combined in our method. We hope to improve picture restoration outcomes by combining these two frameworks and overcoming the drawbacks of single-stage approaches now in use. This framework's DeblurGAN component focuses on resolving the blurring artefacts that are present in the input images. DeblurGAN learns to produce clear and deblurred representations by modelling the degradation process and its inverse using an adversarial training approach. DeblurGAN is an essential step in the restoration workflow since it successfully suppresses blurring artefacts. And it incorporates ESRGAN into the system to enhance the deblurred photos and recover high-frequency information. ESRGAN, which stands for Enhanced Super-Resolution GAN, excels in simultaneously enhancing the quality and super-resolving low-resolution images. By including ESRGAN as the second stage, it is intended to recover fine-grained features and improve the overall visual integrity of the recovered images.

The contributions of the research can be summarized as follows:

- Introducing a Dual-GAN method for restoring images from blurred low-resolution inputs that combines DeblurGAN and ESRGAN
- Demonstrating the effectiveness of our approach in enhancing image quality and recovering fine details.
- Conducting comprehensive experiments and evaluations to showcase the superiority of our Dual-GAN framework over single-stage methods.
- Discussing the limitations and potential future directions for improving image restoration techniques.

The remainder of this paper is organized as follows:

In the subsequent sections, it will provide a comprehensive literature review on image restoration techniques and the advancements in GAN-based approaches. We will then delve into the methodology, explaining the architecture, training process, and modifications made to DeblurGAN and ESRGAN. Following that, the experimental setup, results, and analysis. Finally, we will discuss the implications of our findings, and potential applications, and conclude with future research directions. Through our research, we aim to contribute to the field of image restoration by presenting an innovative Dual-GAN approach that showcases improved performance in restoring image quality from low-resolution blurred inputs.

2. RELATED WORK

2.1. Image Deblurring

Several noteworthy works in the field of image deblurring have been put forth. By utilizing disentangled representations, UID-GAN [1] presents an unsupervised method for picture deblurring, improving the restoration of blurred images. Another method, the Edge Heuristic GAN [2], uses edge heuristics in the model to solve the problem of non-uniform blind deblurring. A model that includes a class-specific prior to improve the restoration quality for various object categories was proposed by Anwar et al. [4]. Salient edges and picture structures are combined by Hu et al. [5]to enhance the quality of deblurred photographs. Wu and Di [6] combine neural networks with a conventional blind deblurring framework and show that their system performs better than end-to-end learning-based approaches.

2.2. Super-Resolution

Different models have been developed in the area of super-resolution. Super-resolution and motion deblurring are both addressed simultaneously by the unified network that the SRDN [3] offers for the restoration of space images. For the restoration of images distorted by median filtering, an adversarial learning approach with cross-domain loss is suggested [8]. Focusing on super-resolving hazy face photos while maintaining identification information, Xu et al. [10]. In order to enhance and restore images quickly, Zamir et al. [7] present a model that learns enriched features. Furthermore, in order to restore and improve image quality while keeping crucial information, Soh and Cho [9] offer a variational deep image restoration model that blends variational auto-encoders and deep networks.

Other image restoration and creation jobs besides deblurring and super-resolution have also been investigated. Improved Image-to-Image Style by using adaptive skip connections, translation enhances picture translation, producing more varied and high-quality generated images [14]. Achieving cutting edge performance in super-resolution applications, ESRGAN [13] presents enhanced super-resolution generative adversarial networks. Semantic image synthesis, which creates realistic images from semantic maps, makes use of spatially adaptive normalisation [15]. For image-to-image translation, conditional adversarial networks have been utilized, enabling the production of multiple outputs based on various input conditions [16]. Despite the fact that these works have made a substantial contribution to the field of picture production and restoration, it is vital to take into account their shortcomings. Some models could be quite computationally complicated, needing a lot of computing power for training and inference.

3. PROPOSED METHODOLOGY

3.1. Overview of The Method

The proposed method uses GAN architecture for image enhancement. In this method, Dual-GAN is used. A DeblurGAN network is used to deblur the input images and then used an ESRGAN (Enhanced Super Resolution GAN) network for super-resolution to enhance the deblurred image. The framework is shown in Fig. 1. The implementation process of this Dual-GAN was as follows:

- The dataset with blurred images was inputted into DebluGAN for training and deblurred images were generated.
- HR images were used to train the ESRGAN and obtain the trained ESRGAN
- The deblurred images that are generated from DeblurGAN were inputted to the trained ESRGAN generator which resulted in enhanced high-resolution images.

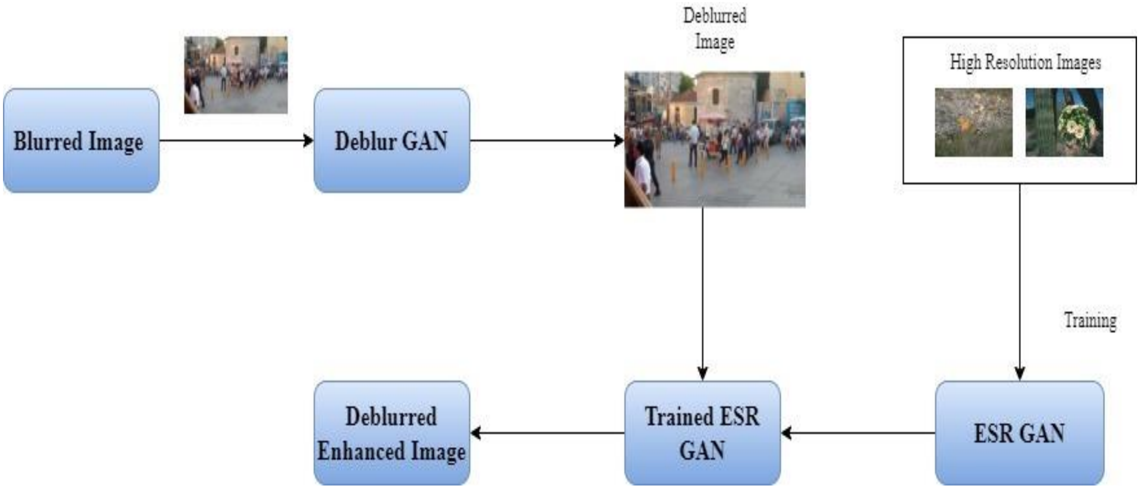

Figure 1: General overview of the proposed framework

3.2. Debluring

The blurring artefacts in the input images are dealt with by the DeblurGAN component. It consists of a discriminator network and a generator network.

Generator network: The DeblurGAN model's generator network is in charge of recovering high-quality images from inputs with low resolution and blur. In order to preserve image features throughout the restoration process, it uses a ResNet block-based architecture. The generator applies reflection padding, convolutional layers, batch normalization, and activation functions like ReLU and tanh to the low-resolution and blurry input images. Multiple Residual blocks are used to gradually improve the quality of the restored image by learning and refining image attributes. By scaling the input image and combining it with the created image, the generator produces the restored image. The generator may produce visually appealing, clear images with fewer blurring artefacts and better details because of this architecture. The architecture is given in figure 2.

Discriminator Network: The DeblurGAN model's discriminator network seeks to discriminate between the generated restored images and the original images. For classification, it applies convolutional layers, batch normalization, leaky ReLU activation, and dense layers. The discriminator learns to distinguish between the generated and ground truth restored images as input. The discriminator can be made more effective such that the generator can be trained to produce restored images that are visually comparable to the original images. In the adversarial training process, the discriminator is essential because it gives feedback to the generator and directs it to produce restorations that are more realistic and visually accurate.

Loss Functions: To streamline the training procedure and produce high-quality picture restoration, the DeblurGAN model makes use of a number of loss functions. First, the L1 loss calculates the mean absolute difference between the ground truth image and the predicted restored image. This loss motivates the generator to provide repaired images with pixel level accuracy. The model also includes perceptual loss, which calculates the mean squared difference between the anticipated and actual images' VGG16 feature representations. This loss encourages visual similarity and improves the restorations' perceptual quality. The similarity between the generated restored image and the distributions of the ground truth images is determined using the Wasserstein loss, also referred to as the Earth-Mover's distance. It promotes the generator to produce outcomes that closely resemble the distribution of the ground truth. The final component of the model is a gradient penalty loss, which penalizes the gradients of the output of the discriminator with respect to interpolated samples between the generated and ground truth images. This loss helps to stabilize the learning process and keeps the generator from being overwhelmed by the discriminator. The DeblurGAN model can successfully repair photos by lowering blurring artefacts, boosting visual quality, and retaining fine details thanks to the combination of several loss functions.

3.3. Super resolution

ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) is a cutting-edge model developed by Xintao Wang et al. It leverages deep neural networks and adversarial training to generate high-quality super-resolution images.

Generator network: The generator network in ESRGAN uses residual blocks to learn the mapping between low-resolution and high-resolution image spaces. This approach is known as deep residual learning. The generator network gradually up-scales low-resolution photos to high-resolution counterparts. It makes use of a number of convolutional layers, activation algorithms (such as LeakyReLU), and pixel shuffle operations to spatially up-sample the image and produce eye catching high-resolution images. The detailed block diagram of the generator is shown in Figure 3.

ESRGAN includes a perceptual loss function to guarantee that the generated images are perceptually similar to the ground truth images. Using a pre-trained VGG network, this loss function calculates the difference in feature representations between the generated and real-world images. The generator is urged to create high-resolution images with correct pixel values as well as visual resemblance in terms of texture, structure, and overall appearance by optimizing this loss

Discriminator Network: A discriminator network is incorporated into ESRGAN to deliver adversarial feedback during training. Distinguishing between manufactured high resolution photos and actual high-resolution photographs is the responsibility of the discriminator network. The discriminative features of the images are learned using convolutional layers, batch normalization, and activation functions (such as LeakyReLU). The generator network is trained to produce high-resolution images that can trick the discriminator into categorizing them as real by optimizing the discriminator. The generator and discriminator networks are trained against one another during the training phase. The discriminator seeks to accurately identify the created and actual high-resolution images, while the generator seeks to create high-resolution images that can fool the discriminator. This adversarial training procedure improves the generator's capacity to generate realistic and aesthetically acceptable high-resolution images.

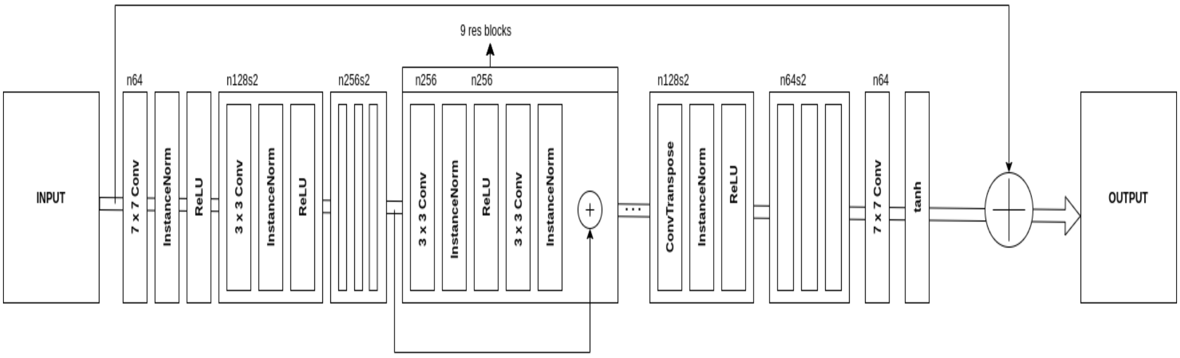

Figure 2: Generator of DeblurgGan

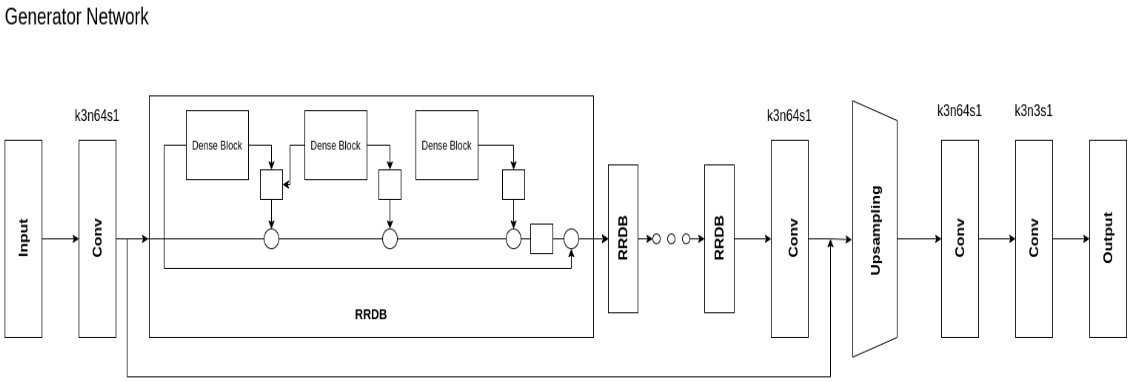

Figure 3: Generator of ESRGAN

4. EXPERIMENTS AND ANALYSIS

4.1. Datasets

The GoPro dataset was used to train the DeblurGAN model. For image deblurring tasks, the GoPro dataset is a frequently used benchmark dataset. It is made up of a sizable number of photographs that are hazy and low-resolution that were taken using GoPro cameras in a variety of actual outdoor scenarios. The DIV2K dataset was used to train the ESRGAN model. A high-quality dataset created especially for single image super-resolution tasks is the DIV2K dataset. It provides a trustworthy baseline for assessing super-resolution algorithms and includes high-resolution photographs with a variety of information. The Set5 dataset was utilized to assess both models' performance. Five excellent photographs make up the well-known benchmark dataset known as Set5, which is frequently used to assess image super-resolution methods. For quantitative evaluation, it offers a standardized set of photos with high-resolution ground truth references.

4.2. Evaluation Metrics for Image Quality: PSNR and SSIM

PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are widely used objective metrics for assessing the quality of images and videos.

PSNR measures the ratio of the maximum possible power of a signal to the power of added noise or distortion. It is straightforward to interpret, with higher values indicating better quality. However, PSNR is sensitive to compression artefacts and may not correlate well with human perception.

SSIM, on the other hand, incorporates elements of human visual perception by measuring structural similarity between the original and distorted images. It considers luminance, contrast, and structural information, providing a more perceptually relevant evaluation. SSIM has shown a better correlation with human perception, particularly for measuring structural distortions and artefacts.

Qualitative results are shown in Figure 4

4.3. Result

Figure 4 a, d, g and j demonstrates the input images used in our experiments. These images represent a diverse range of scenes, including natural landscapes, objects, and people. Figure b, e, h and k represent the output images generated by our dual GAN model. Figure c, f, i and l presents the sharp images which serve as the ground truth, providing a reference for evaluating the performance of our deblurring model.

(a) Bulrred Image (b) Restored Image (c) Sharp Image

(d) Bulrred Image (e) Restored Image (f) Sharp Image

(g) Bulrred Image (h) Restored Image (i) Sharp Image

(j) Bulrred Image (k) Restored Image (l) Sharp Image

Figure 4: Qualitative results

5. DISCUSSION

The generator network of a GAN is in charge of enhancing the input image while improving image clarity. It attempts to produce a clearer, higher-quality output image from a blurry and low-quality input image. The generator network architectural components learn to transform the input image. In this Dual-GAN method residual block is responsible for removing the blur in the input image and the dense residual block enhances the deblurred image.

The discriminator network serves as a judge and attempts to discern between authentic, high-quality images and those produced by the generator network. The discriminator and generator networks engage in a mini-max game during training. This adversarial training dynamic helps the generator network learn the underlying patterns and structures that contribute to image clarity.

The proposed method is compared to DeblurGAN, DeblurGAN-v2, and Edge Heuristic GAN in Table 1. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are the evaluation metrics employed.

First, let's analyse the PSNR values. It can be observed that the proposed method Dual GAN achieves the highest PSNR value of 32.01, indicating superior performance in terms of pixel-wise reconstruction accuracy compared to the other methods.

However, when considering the SSIM values, the proposed method has a value of 0.906 compared to DeblurGAN, Edge Heuristic GAN, and DeblurGAN-v2. SSIM measures the structural similarity between images, including texture, edges, and perceptual information.

Table 1: Comparisons on the GoPro dataset

Method	PSNR	SSIM
DeblurGAN [11]	28.70	0.858
Edge Heuristic GAN [2]	29.32	0.933
DeblurGAN-v2 [12]	29.55	0.934
Dual GAN (Ours)	32.01	0.906

6. CONCLUSION

In this study, a dual GAN model was put forward, and it has demonstrated promising results in the tasks of super resolution and image deblurring. The model is able to improve and restore the quality of fuzzy and low-resolution photographs using the strength of generative adversarial networks, producing outputs that are visually appealing and high fidelity. In terms of image quality, sharpness, and fine detail retention, experimental results on benchmark datasets, such as the GoPro dataset for deblurring and the DIV2K dataset for super-resolution, have shown considerable gains over existing approaches. It's crucial to recognize the dual GAN model's limitations, though. The training procedure can be computationally taxing and demand a lot of time and resources. In addition, the model's performance may be affected by the quality and diversity of the training dataset. Further research is needed to explore strategies for handling video deblurring and different types of blurring or scaling factors in super-resolution tasks.

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