

Image Quality Enhancement Method Based on Generative Adversarial Network

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Abstract

The image acquisition and transmission process can easily lead to a reduction in image quality and bring noise, which makes the readability of the image worse. In order to remove the noise in low-quality images and restore more image details, this paper proposes a generative adversarial network for image quality enhancement. The generator can generate a more realistic image, restore the lost image details in the image, and reduce noise through the noise module. Use content loss, adversarial loss and MSE loss as loss functions to constrain the optimization of network parameters. Experiments show that this method has better performance than other methods.

Keywords

Image quality enhancement; Denoising; GAN.

1. Introduction

Images record our lives, especially with the popularization of smart phones, users enjoy the fun of recording more. Although the resolution of mobile phone cameras is getting higher and higher, the cameras we currently use still have limitations. In many scenarios, the images captured by the camera cannot meet our requirements, and such situations are often caused by environmental influences. This requires the computer to be able to recover the original scene from the defective scene [1, 2]. These images that need to be restored usually have various problems, or there are noises, or information is missing. Image enhancement is one of the preprocessing steps of various computer vision applications, which is a process to improve image quality without losing any information. For example, in the field of medical images, contrast enhancement is often used to improve image quality. The basic feature of contrast enhancement is to enhance the pixel brightness of images in medical applications. Image enhancement technology is used in various computer vision tasks. For different vision tasks, images need to use different image enhancement methods. At present, image enhancement technology is not only widely used in scientific research, military and other fields, but many civilian devices have begun to use computer vision equipment with image enhancement functions.

There are many factors that cause image degradation, such as the aberration of the optical system, the relative movement of the imaging process, the spreading characteristics of X-rays, the interference of various external factors, and noise [3]. This chapter discusses only two types of point degradation and spatial degradation. The so-called point degradation is that degradation factors only affect the gray level changes of pixels in the image, while spatial degradation is that degradation factors cause spatial blur. These two degradations can generally be described by mathematical degradation models. A complex factor that causes image degradation is random noise. In the process of forming a digital image, noise will inevitably be added. When we consider the problem of image restoration in the presence of noise, we must know the statistical characteristics of the noise and the correlation between the

noise and the image signal, which is very complicated. In practical applications, it is often assumed that the noise is white noise, that is, its spectral density is constant and not related to the image [4]. This assumption is ideal because the concept of white noise is a mathematical abstraction.

With the rapid development of multimedia technology, still images are more and more widely used. Its application mainly focuses on image storage and image transmission. From specific applications, we can find that still images occupy more and more resources. Under such background conditions, the compression of still images has become a research hotspot. With the development of multimedia technology, users or enterprises have to transmit a large number of images every day. In the process of image data transmission, it is easy to cause the loss of image information, resulting in a decline in image quality, and affecting visual perception. However, uncompressed image transmission requires a lot of network resources, so it is of practical significance to propose an image quality enhancement algorithm.

2. Related Work

With the development of deep learning technology, a large number of network frameworks with excellent performance have been proposed. The generative adversarial network is composed of a generator and a discriminator. The generator can generate realistic images, and the discriminator can determine whether the generated images are true or false. When the discriminator cannot distinguish the true and false of the generated image, the generated image has high quality [5].

The purpose of image denoising is to restore the corresponding original image from the noisy image. Specifically, let $f \in R^{N \times N}$ and $u \in R^{N \times N}$ denote the noisy and corresponding uncontaminated image samples respectively. The relationship between the two is:

$$O: f \rightarrow u$$

Where O is the mapping function from the noisy space to the original space.

In traditional denoising methods, the mapping function is usually constructed based on the spatial domain or the transform domain [6]. Spatial denoising directly affects pixels. Common denoising methods include mean and median filtering, which replaces the pixel value with the mean/median value of a certain pixel neighborhood. However, the spatial denoising method has poor noise universality and the image details are easy to lose. To solve this problem, a transform domain denoising method is proposed, which is based on Fourier or wavelet transform methods to map the spatial image to the transform domain in order to effectively separate the noise, thereby improving the denoising effect [7, 8, 9].

As a typical representative of the adversarial learning model, GAN is widely used in the field of denoising. It is composed of a generator G and a discriminator D [10, 11]. The structure is shown in Figure 1. Among them, the generator G receives the noisy image and pre-denoises it to generate the image $G(f)$; the discriminator D takes the original image u and $G(f)$ as input, and its output gives the original image a higher value to generate Image $G(f)$ has a lower value. Training G and D iteratively based on the constructed loss function, forcing $G(f)$ to gradually approximate the real image, and finally making D unable to accurately distinguish the original and generated images, thereby completing denoising. The commonly used objective function is the maximum-minimum value game between the two, namely:

$$\min_G \max_D L_{GAN}(D, G) = E_{u \sim P_u} [\log D(u)] + E_{f \sim P_f} [\log(1 - D(G(f)))]$$

Where $E(\cdot)$ is the expectation operator, $\log D(u)$ is the probability that the discriminator D correctly recognizes the real image, $\log(1 - D(G(f)))$ is the probability that D will recognize the

generated image as a false image. Based on this counter loss, the generator and discriminator can be adjusted inversely to improve the denoising performance. However, this counter-loss easily leads to high-frequency artifacts and cannot maintain subjective feature information.

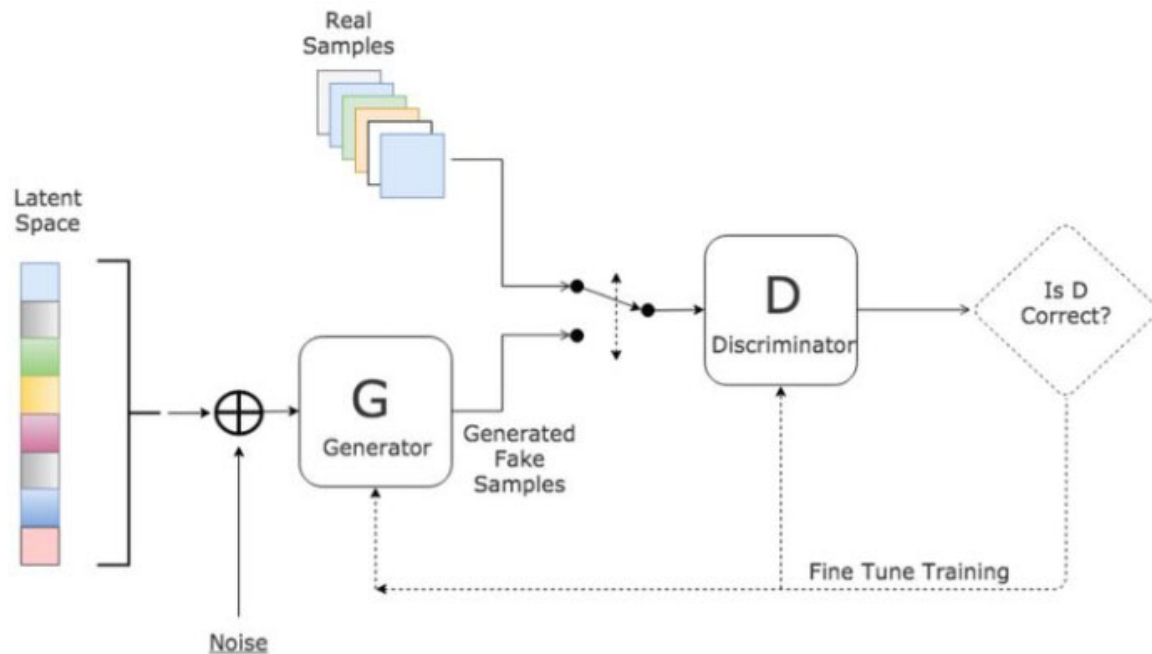


Figure 1. Generative Adversarial Network

3. Method

3.1. The Network Framework

Images often contain rich information, and high-quality images are conducive to information acquisition. At present, the images directly obtained from the network are often in JPG format. Due to the storage characteristics of the JPG image format, it is easy to cause the loss of information in the image and generate noise, which causes image distortion and serious degradation of image quality. However, direct storage of uncompressed images requires a large amount of resource space. The degraded image brings difficulties to the information acquisition in the image and does not meet the characteristics of the human eye. How to improve the quality of JPG image and improve the human visual effect of JPG image is an urgent problem to be solved at present.

The generator consists of 6 convolution modules, such as Conv1, Conv2,...,Conv6. Among them, Conv1 is used to extract low-level features from the input image, Conv2, Conv3,..., Conv5 is used to extract deep features of the image, and Conv6 reduces the number of channels of high-dimensional features to 3 and outputs the image. In the generator of the present invention, a noise map is added after the input image, thereby achieving a certain noise reduction effect and improving the robustness of the network. The residual structure is adopted in the generator, which alleviates the problem of gradient disappearance caused by increasing the depth in the deep neural network, and at the same time makes the network easier to train.

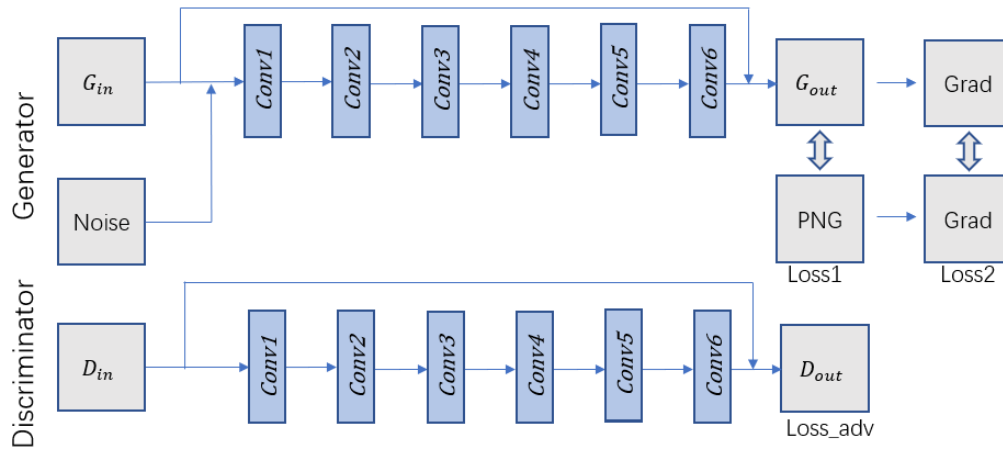


Figure 2. The network framework

3.2. Loss Function

Use a new loss function to optimize the network parameters. Suppose the image output by the generator is G , the gradient image for G is denoted as $M(G)$; the high-quality PNG image is set as Y , and the gradient image for Y is denoted as $M(Y)$. In the traditional image quality enhancement network, MSE loss is generally used. Although it is easy to get a higher peak signal-to-noise ratio (PSNR), it is easy to cause image blur, leading to the problem of lack of high-frequency details of the image. Therefore, we use a pre-trained VGG network to calculate the characteristic Euclidean distance between the generated image and the high-quality PNG image, denoted as l_{vgg} , as follows:

$$l_{vgg} = \frac{1}{WH} \sum_x \sum_y (vgg(G) - vgg(Y))^2$$

After calculating the gradient of the JPG image and the PNG image, the difference image between $M(G)$ and $M(Y)$ is shown in Figure 3. The interpolated image directly shows the presence of noise in the degraded image. Therefore, this paper uses the L1 loss to calculate the loss between $M(G)$ and $M(Y)$, denoted as l_m as follows:

$$l_m = \frac{1}{WH} \sum_x \sum_y |M(G) - M(Y)|$$

The adversarial loss is used to improve the discriminator to distinguish JPG images from PNG images. When the discriminator cannot distinguish between the JPG image and the PNG image, it means that the quality of the image G generated by the generator is equivalent to that of Y . The adversarial loss is recorded as l_{adv} , as follows:

$$l_{adv} = \sum_n -\log(D(G))$$

In summary, the loss function l proposed in this paper is recorded as:

$$l = \alpha \cdot l_{vgg} + \beta \cdot l_m + \gamma \cdot l_{adv}$$

In the above formula, α , β , and γ represent the hyperparameters of l_{vgg} , l_m , and l_{adv} , respectively, and are used to adjust the respective proportions of l_{vgg} , l_m , and l_{adv} .

4. Experiment

4.1. Training

The experimental equipment used Intel(R) Xeon(R) E6-2683 processor, Titan X graphics card, PyTorch, CUDA9.0 and CUDNN7.1 to accelerate model training. We use RENOIR, DND, and SIDD as training sets to train the network.

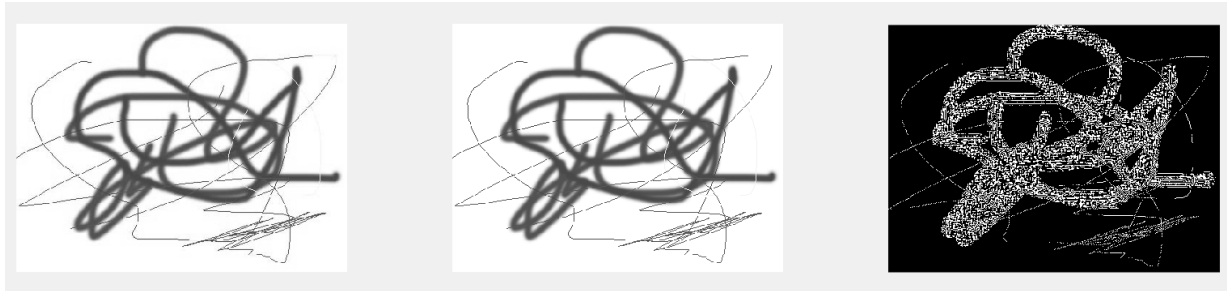


Figure 3. Noisy image

The image above is the original image and the degraded image, the third image is the difference between the original image and the noise image, and the noise image.

4.2. Experiment Analysis

In order to objectively illustrate the performance of the algorithm in this paper, we use Nam and PolyU datasets as the test set. Three indicators are used to evaluate the processed image: structural similarity, peak signal-to-noise ratio, and MSE [12].

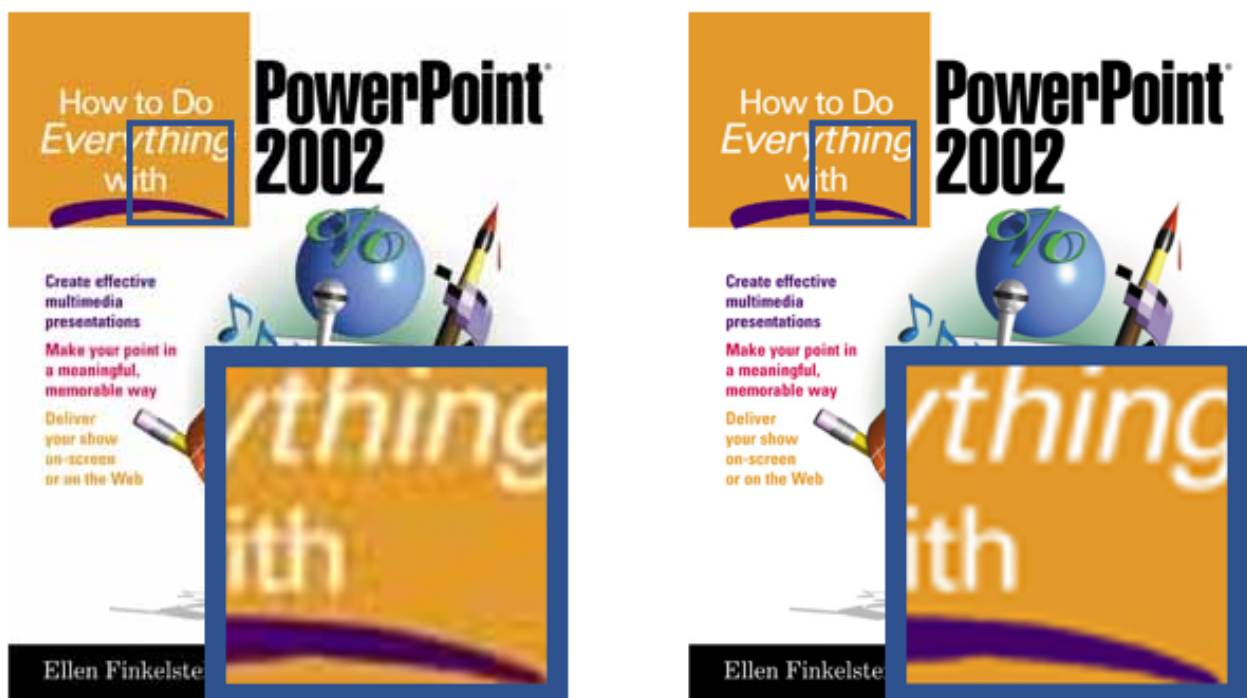


Figure 4. Zoom in on the details of the image quality enhancement example

Figure 4 is a display of the enhancement effect of low-quality images. The details in the blue box area restore the surface. The method proposed in this paper is effective. We use the test set to more fully test the method proposed in this article, as shown in Table 1.

Table 1. Comparison between different algorithms

Methods	Nam			PolyU		
Indexs	PSNR	SSIM	MSE	PSNR	SSIM	MSE
ATM	32.21	0.813	0.041	32.89	0.818	0.040
CAP	33.86	0.877	0.025	34.15	0.896	0.021
GFN	33.97	0.914	0.034	34.98	0.915	0.035
Ours	35.45	0.951	0.015	36.54	0.984	0.011

The number nine in Table 1 shows that this method has obvious advantages over other methods. The PSNR and SSIM indexes of the method in this paper are higher than other methods, indicating that the image restored by the method in this paper has better visual effects. The MSE of the method in this paper is lower than other methods, indicating that the method in this paper has stronger objectivity.

5. Conclusion

Image degradation is caused by a variety of miscellaneous reasons. How to improve image quality and thereby improve the visual effect of the image is one of the current problems that need to be solved. This paper proposes an image quality enhancement algorithm based on the generative adversarial network, which can better remove the noise in the image and restore the details in the image.

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