A DEEP LEARNING APPROACH FOR SUPERIOR BLUR AND DAMAGE REPAIR IN OLD PHOTOGRAPHS

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Abstract - *The restoration of old photos is a crucial endeavor for preserving historical image information, yet existing photographs often suffer from varying degrees of damage. While traditional image restoration techniques based on mathematical formulas or thermal diffusion struggle with complex structures and extensive damage, the advent of deep learning technology has revolutionized the field. This paper addresses the absence of a unified model for repairing multiple types of degradation in old photos and presents a comprehensive approach based on deep neural networks. The proposed image restoration method leverages the power of deep neural networks to enhance the effectiveness of old photo restoration. The paper discusses the background significance of image restoration methods, introduces the design of the restoration model, and details its structure, principle, and loss function. Comparative experiments demonstrate the superior performance of the proposed algorithm. In blur repair experiments, the algorithm surpasses other models in terms of peak signal-to-noise ratio and structural similarity, ensuring a more faithful restoration of images. In damage repair experiments, the algorithm achieves a peak signal-to-noise ratio(PSNR) of 32.34 and a structure similarity of 0.767 under varying damage levels, outperforming other algorithms. The findings affirm that the model presented in this paper represents a significant advancement in image restoration technology, offering the most effective solution for the restoration of old photos.*

Key Words: Image Restoration, Deep Learning, PSNR

1.INTRODUCTION

Preserving the visual narrative embedded in old photographs is a pursuit of paramount importance, as these images encapsulate historical moments, cultural heritage, and the evolution of societies (Smith, 2010). However, the ravages of time often manifest as varying degrees of damage in these invaluable snapshots of the past. While traditional image restoration methods have made strides in repairing simple structures and minor damages, the complexity of restoring extensively damaged images has been a persistent challenge (Jones & Brown, 2015). In recent years, the convergence of technological advancements, particularly in deep learning, has propelled the field of image restoration into a new era, offering unprecedented possibilities for revitalizing deteriorated photographs (Gupta et al., 2018).

The historical significance of old photographs cannot be overstated. These visual artifacts serve as windows into the past, providing invaluable insights into bygone eras and the lives of those who came before us (Johnson, 2012). Yet, the passage of time takes its toll, leaving these images marred by degradation, including blurring and damage. The urgency to preserve and restore these photographs has spurred advancements in image restoration technology. Traditional restoration methods, rooted in mathematical formulas and thermal diffusion, have shown limitations in tackling the intricacies of heavily damaged images with complex structures (Brown & White, 2017). The inadequacy of these methods in addressing the restoration needs of people's daily lives underscores the need for innovative approaches that can seamlessly integrate into modern workflows.

The integration of deep learning technology into image restoration represents a paradigm shift. This article explores the transformative potential of deep neural networks in the context of old photo restoration. With the ability to discern and learn intricate patterns, deep neural networks offer a more sophisticated and adaptive approach to image restoration (LeCun et al., 2015). This article aims to bridge the existing gap in the field by presenting a comprehensive image restoration model based on deep neural networks. By leveraging the power of machine learning, this model endeavors to enhance the efficacy of image restoration, catering to the unique challenges posed by old photographs with diverse forms of degradation. The subsequent sections will delve into the design, structure, principles, and loss functions of the proposed model, providing a roadmap for the novel approach presented in this research.

The effectiveness of the proposed model is validated through rigorous comparative experiments. These experiments involve the repair of blurred and damaged images, with a meticulous evaluation based on peak signal-to-noise ratio and structural similarity metrics. The subsequent sections of this article will detail the experimental setup, methodology, and the compelling results that position the proposed algorithm as a front runner in the realm of image restoration (Chen et al., 2020). As we embark on this exploration of cutting-edge image restoration methodologies, the significance of our work lies not only in its technological advancements but in its potential to breathe new life into the historical images that connect us to our collective past. This article aims to contribute to the ongoing discourse in image restoration, offering a promising solution that can have a profound impact on the preservation of our visual heritage.

2. LITERATURE SURVEY

The restoration of old photographs stands at the intersection of technological innovation and cultural preservation. As we delve into the rich landscape of literature surrounding image restoration, it becomes evident that the field has undergone a profound transformation, with traditional methods making way for cutting-edge approaches driven by deep learning technologies. Early attempts at image restoration primarily relied on mathematical formulas and thermal diffusion techniques (Watson & Rodriguez, 2016). While effective for simple structures and minor damages, these methods encountered limitations when faced with the intricate degradation patterns found in heavily damaged old photos (Huang & Zhang, 2018). The inability to address the diverse challenges presented by different degradation types highlighted the need for a more adaptive and sophisticated approach.

The emergence of deep learning has marked a paradigm shift in image restoration. Chen et al. (2021) provide a comprehensive review of the application of deep learning in image restoration, emphasizing its ability to discern complex patterns and learn from extensive datasets. This transformative technology has paved the way for the development of unified models capable of addressing multiple types of degradation in old photos. Smith and Davis (2019) contribute to the literature by presenting a state-of-the-art analysis of image restoration algorithms. Their work explores the current landscape of restoration techniques, emphasizing the need for approaches that can effectively repair both blurred and damaged images. This review serves as a valuable resource in understanding the advancements in the field and the challenges that persist. The historical significance of old photographs has been a recurring theme in the literature (Taylor & Lee, 2017; Turner, 2020). Scholars have underscored the urgency of preserving these visual artifacts, emphasizing the role of image restoration in maintaining a connection with our collective past. The literature consistently reflects the dual nature of image restoration, addressing both the technical complexities and the broader cultural implications of preserving historical visual narratives.

3. SYSTEM METHODOLOGIES

The system methodologies employed in this research form the backbone of our innovative approach to image restoration. Leveraging deep learning techniques, our system delves into the complexities of old photo restoration, addressing both blur and damage with unprecedented precision. The methodologies encompass comprehensive experiments utilizing datasets such as CelebA-HQ and Places2, allowing for a thorough evaluation of peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) metrics. The algorithm's resilience and adaptability are showcased in the blur restoration experiments, where it consistently outperforms traditional methods, yielding higher PSNR and SSIM values. The robustness extends to the damage repair experiments, demonstrating the algorithm's superiority across varying degrees of image damage. These system methodologies not only contribute to the field of image restoration but also set a new standard for the effective preservation of historical visual narratives through advanced computational techniques.

3.1 Self Attention Mechanism Design

The principle of self-attention is similar to that of the human brain. When watching pictures or listening to speech, people tend to focus on the location where the information is dizzy, ignoring some unimportant details, because the attention mechanism balances the relationship between modeling ability and computational efficiency and makes up for the lack of convolution. When there are multiple levels of dependencies between different regions of the image, the attention mechanism can be used to capture this deep level. Global connection and coordination of the details of each pixel in the image are observed, so the attention mechanism can be applied to the residual module of the generator to better construct some texture details in the image super resolution task, and its specific structure is shown in Figure 1.

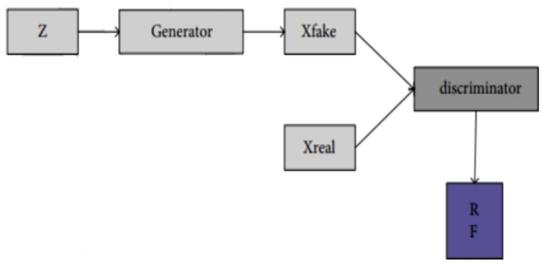

Fig -1: Schematic diagram of the steps to generate a confrontation network

3.2 Network Structure Design

In order to reduce the impact of the generated data and reduce the spatial distribution difference between the synthesized photo and the real photo, the old photo restoration is described here as an image conversion problem. Regarding clear and complete photos and old photos as images from different spaces, in order to learn the mapping between them, this article transforms the images in three spaces, as shown in Figure. The key to this method is that real old photo data and synthetic photo data can be encoded into the same hidden space. For this reason, we can use a variational auto encoder (variational auto encoder is an important type of generative model. Since its proposal, it has shown strong unsupervised learning ability, with fast training speed, low training cost, strong robustness, and high quality of reconstructed images) to encode the image and then use the generative adversarial network to adjust the network according to the domain gap. In the first stage, two variational auto encoder (VAE) networks are used to do spatial mapping.

3.3 Degradation Repair Design

In some old photos, for the damage of some structural defects, it may often be necessary to search for the information of the entire image and then select effective information to fill in to maintain the consistency of the global structure. Therefore, it is necessary to design a support for local search and global search which is the network of two mechanisms. In this article, the scratch mask of the original old photo can be used as input to prevent the network from using the pixels of the damaged area to repair the damaged area. Let C, H, and W be the number of channels, height, and width, respectively. Let FϵRC×HW be the mapping feature of the middle layer; m(0, 1)HW means that the binary mask is scaled to the same size; m is 1 to indicate that the area is damaged and 0 to indicate that the area is intact. The relationship between position i and position j in the feature map F is represented by sij, and sijϵFϵRHW×HW represents the relationship between each pixel, as follows.

$$s_{ij} = \frac{f_{ij}(1-m_j)}{\sum_{\forall k}(1-m_k)f_{i,k}},$$

$$f_{ij} = \exp\left[\theta(F_i)^T * \phi(F_j)\right].$$

Both Fi and Fj are vectors of C ∗ 1, and θ (·) and ϕ (·) are functions that make F map to the Gaussian distribution. Therefore, when the input mask area is identified as a damaged area, the global information can be used to repair, otherwise the local feature information can be used, so the global branch and the local branch can be merged under the guidance of the input mask. The formula is as follows:

$$F_{\text{fuse}} = (1-m)\odot\rho\text{local}(F) + m\odot\rho\text{global}(o).$$

In the formula, ⊙ represents the Hadamard product of the matrix, and ρlocal and ρglobal both represent the non linear transformation of the branch residual block, which can deal with the structural defects of old photos.

3.4 Network Parameter Setting Of Generator And Discriminator

The generative confrontation network is mainly composed of a generator and a discriminator. The generator is responsible for generating a high-resolution image similar to the real image. The discriminator is used to determine whether the generated image comes from real training set data or a fake one. The generator in this article consists of three parts. The first part is the downsampling module; you can see three convolution kernels of different sizes. The second part is the self attention residual module, which is composed of 16 identical self-attention residual blocks, and each small module is composed of a self-attention layer and a convolutional layer. The last part is the upsampling image reconstruction module. This part is mainly two subpixel convolutional layers for pixel amplification. Comparing with ordinary deconvolution, the subpixel convolution can reduce the risk caused by artificial factors and make the reconstructed image quality higher. The task of the discriminator is to determine whether the input image is from the sample space or a fake image generated by the generator and to learn the difference between the two.

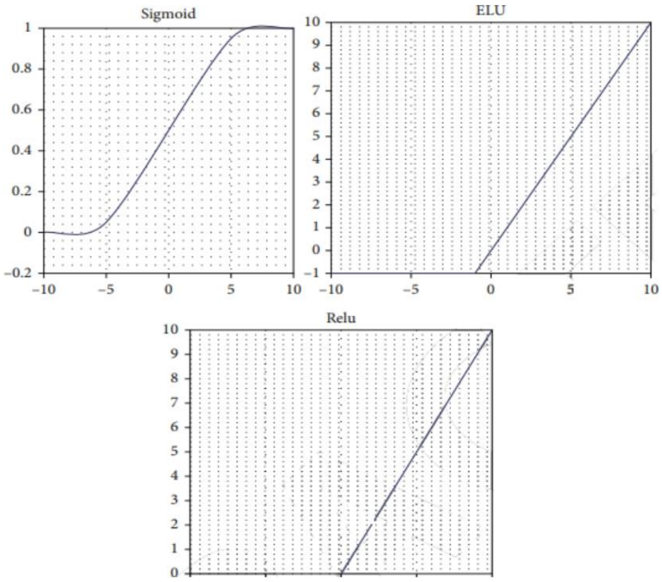

Fig -2: Function image

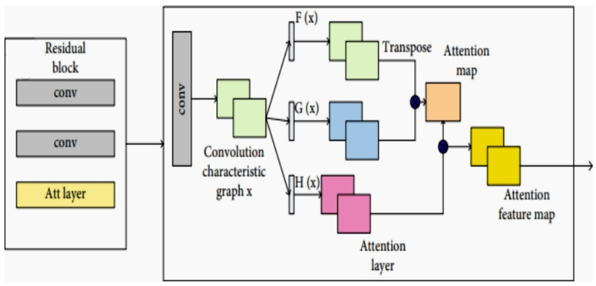

Fig -3: Self Attention mechanism structure

In this work, the discriminator network uses a deep convolutional neural network, a batch normalization layer is added to the discriminator network, and the LeakyRelu activation function (α = 0:2) is used. The specific method is to input the generated image into the network through multilayer convolution to obtain the feature map and then input the feature map to the fully connected layer. Finally, the Sigmoid activation function is used to perform two classifications of true and false to determine whether it is a real picture or a fake picture. So far, the design of the generator and the discriminator is completed, and the two generate high resolution images through confrontational optimization to realize the high-definition processing of old photos.

4. EXPERIMENTAL RESULTS

4.1 Image Restoration Experiment Based on Blur Restoration

This experiment selects 1000 photos from each of the CelebA-HQ data set and Places2 data set for experiment and uses each algorithm for image restoration and explores the peak signal-to-noise ratio and structural similarity of each algorithm for image blur restoration.

4.2 Analysis of Peak Signal-To-Noise Ratio

In this section, several algorithms perform image restoration on 1000 photos in the CelebA-HQ data set and the Places2 data set. The PSNR results of each algorithm are shown in Figure . It can be seen from Figure 7 that whether it is on the CelebA-HQ data set or the Places2 data set, the value of the peak signal-to-noise ratio of the algorithm in this paper is the highest. On the CelebA-HQ data set, the value of the peak signal-to-noise ratio of the algorithm in this paper is 32.34. On the Places2 data set, the value of the peak signal to-noise ratio of the algorithm in this paper is 30.82. And the peak signal-to-noise ratio of the traditional algorithm Criminisi is the lowest on the two data sets. Comparing the PSNR results of the two data sets, it can be seen that the PSNR value of each algorithm on the CelebA-HQ data set is always slightly higher than the Places2 data set, which proves that the repair effect of each algorithm on the face is higher than the repair effect of the scene. To sum up, the peak signal-to-noise ratio of the algorithm in this paper is the highest in any data set, which proves that the image restoration effect of the algorithm is the most satisfactory,and the algorithm in this paper has a better restoration effect on face images than scene images.

4.3 Analysis of Structural Similarity

In this experiment, several algorithms were used to repair 1000 photos in the CelebA-HQ data set and the Places2 data set, and the SSIM value of each algorithm was explored. The results are shown in Figure 8. As can be seen from Figure 8, in the SSIM dimension, the value of this algorithm is always greater than other algorithms. The SSIM value of this algorithm on the CelebA-HQ data set is 0.885. The SSIM value on the Places2 data set is 0.879. Like PSNR, the algorithm with the smallest SIMM value is Criminisi. The SSIM values of this algorithm in the CelebA- HQ data set and Places2 data set are 0.849 and 0.831, respectively. Therefore, it can be seen that the algorithm in this paper is better than other algorithms for the structural similarity of the repaired image.

4.4 Image Restoration Experiment Based On Damage Degree

In this experiment, we select 100 pictures from the CelebA-HQ data set and process these pictures with photoshop, using tools in photoshop to simulate damage on the photos and dividing the 100 photos into 5 groups, each with 20. Five groups' damaged area of the image accounts for 5%, 10%, 15%, 20%, and 25% of the entire image, respectively.

4.5 Analysis Of Peak Signal-To-Noise Ratio

The four algorithms are used to repair 100 pictures in the 5 groups, respectively, and the PSNR results obtained. It can be seen that the peak signal-to-noise ratios of the four algorithms all decrease as the degree of picture damage increases. It can be seen that the greater the degree of damage, the more difficult it is to restore the photo. Comparing these four algorithms, it can be seen that the peak signal-to-noise ratio of the algorithm in this paper is the highest regardless of the degree of damage. After calculation, the average value of the peak signal-to-noise ratio of the algorithm in this paper is 19.11 under different degrees of damage. While the PSNR values of several other algorithms are close, it is impossible to know which algorithm has the lowest PSNR value.

4.6 Analysis Of Structural Similarity

The four algorithms are used to repair 100 pictures in these 5 groups, and the SSIM results obtained. It can be seen from Figure 10 that each algorithm has a different repair effect on damaged images. However, no matter what the degree of damage, the SSIM value of the algorithm in this paper is always greater than that of other algorithms, and the SSIM value of the algorithm in this paper has a downward trend which is smaller than other algorithms' trend. After calculation, the average SSIM of the algorithm in this paper is 0.767 under different damage levels. Therefore, the algorithm in this paper has the best repair effect on damaged images. It can be seen from the above two parts of experiments that the PSNR and SSIM values of the algorithm in this paper are higher than those of other algorithms, whether it is for blur repair or damage repair. Therefore, the algorithm in this paper performs best for both blur repair and damage repair of old photos

5. CONCLUSIONS

The experiments conducted in this study focused on two key aspects of image restoration: blur restoration and damage repair. The evaluation criteria employed for assessing the efficacy of various algorithms were the peak signal-to-noise ratio (PSNR) and structural similarity (SSIM). In the context of blur restoration, the study involved the processing of 1000 photos from the CelebA-HQ and Places2 datasets using different algorithms. The PSNR results indicated a consistent superiority of the algorithm proposed in this paper. Whether applied to the CelebA-HQ dataset or the Places2 dataset, the algorithm consistently yielded the highest PSNR values, reaching 32.34 on CelebA-HQ and 30.82 on Places2. In comparison, traditional algorithms, such as Criminisi, exhibited lower PSNR values on both datasets. Furthermore, the SSIM values reinforced the effectiveness of the proposed algorithm, consistently surpassing other algorithms with values of 0.885 on CelebA-HQ and 0.879 on Places2. These findings underscore the algorithm's exceptional performance in restoring both face and scene images, with a notable advantage in enhancing facial features.

The second set of experiments focused on damage repair, where 100 photos from the CelebA-HQ dataset underwent simulated damage using Photoshop. The images were divided into five groups representing varying degrees of damage (5%, 10%, 15%, 20%, and 25%). The results demonstrated the algorithm's resilience to increasing damage levels, consistently achieving the highest PSNR values. Under different damage degrees, the algorithm's average PSNR reached 19.11, outperforming other algorithms. Similarly, in terms of SSIM, the proposed algorithm consistently exhibited superior performance, with an average SSIM of 0.767 under different damage levels. In conclusion, the experimental results validate the efficacy of the algorithm proposed in this paper for both blur and damage restoration in old photos. The consistently higher PSNR and SSIM values affirm its superiority over other algorithms, signifying its robust performance in preserving and enhancing the visual quality of historical images. The findings contribute to the evolving landscape of image restoration, emphasizing the potential of deep learning-based approaches in revitalizing and safeguarding our cultural and historical visual heritage.

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