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Overview of Digital Image Restoration

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Abstract: Image restoration is an image processing technology with great practical value in the field of computer vision. It is a computer technology that estimates the image information of the damaged area according to the residual image information of the damaged image and carries out automatic repair. This article firstly classify and summarize image restoration algorithms, and describe recent advances in the research respectively from three aspects including image restoration based on partial differential equation, based on the texture of image restoration and based on deep learning, then make the brief analysis of digital image restoration of subjective and objective evaluation method, and briefly summarize application of digital image restoration technique in the future and prospects, provide direction for the research on image after repair.

Keywords: Image inpainting, variational PDE, texture, evaluation method.

1 Introduction

Bertalmio et al. first proposed the concept of image restoration technology in 2000 [Bertalmio, Sapiro, Caselles, et al. (2000)]. Their research is based on the inpainting algorithm of partial differential equation, which spreads the edge information of the damaged area of the image to the small scale damage repair of the region to be repaired, so as to achieve the repair effect invisible to the human eye. With the development of technology, image restoration technology has greater practical value, which makes the research and application of image restoration reach a leap forward. Therefore, image restoration technology has become a research hotspot in computer graphics and computer vision.

Generally speaking, there are many factors that can cause local information defects in digital images [Shugen (2004)].The repair algorithm based on partial differential equation (PDE) was first proposed to apply to small-scale damage repair of images. For large-scale damage repair of images, text-based image repair algorithm appeared. The most commonly used algorithm was Criminisi algorithm [Criminisi, Perez and Toyama (2004)]. With the rise of deep learning, in order to improve the repair effect and

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strengthen the limitation of traditional algorithm in content repair, researchers are committed to the research of image repair algorithm based on convolutional neural network and the generate antagonism network.

In addition, the repair model in image restoration technology only USES the undamaged region information to estimate and predict the region to be repaired according to the law of human visual psychology. Therefore, the predicted solution is not the only one, and the repair effect can be invisible to the human eye.

2 Related work

2.1. Image restoration based on variational PDE

Variational PDE based image restoration is a non-texture image restoration method suitable for small area damage, while for large incomplete images, due to the loss of too much information, the repair effect of this method is not good. The main idea is to use the edge information to be repaired to spread some distance to the damaged area along the normal direction of the isolux line, as shown in the figure below.

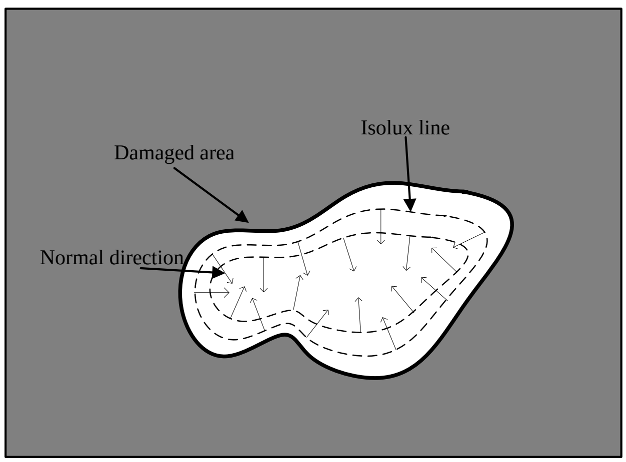

Figure 1: Variational PDE algorithm for image restoration

Aiming at the defects of texture restoration, Yong et al. proposed a new PDE framework for the restoration of fringe texture images [Zhu, Wang and Han (2009)]. The main idea is to use the direction field as the constraint of diffusion direction. Once the direction field can be estimated correctly, the gray information can be propagated to the damaged area along the local positioning direction. However, this model is not enough to repair the detailed features. In addition, Li et al. proposed a diffusion-based digital image restoration region localization method, and constructed a feature set based on local variance within and between channels to identify the restoration region. The purpose of this method is to judge whether the image is forged or not. The stronger the designed classifier is, the greater contribution it will make to image restoration [Li, Luo and Huang (2017)].

In the following research, many image repair algorithms based on variational PDE are developed. It mainly includes total variation (TV) model [Chan and Shen (2001)], Euler's elastica model [Chan, Tony, Kang et al. (2002)], Mumford-shah model [Tsai, Yezzi and Willsky (2001)] and Mumford-Shah-Euler model [Esedoglu and Shen (2002)]. These models are introduced into image restoration by TV (total variation) denoising or MS (Mumford-Shah) segmentation model and other variational models, which are not ideal for image boundary restoration.

2.2 Image restoration based on texture

Image restoration method based on texture, can repair any damaged scale, its basic idea is the damaged area on the edge of the texture block as a template, choose from known image and template match most texture image block, copy to templates area, to ensure the texture structure similarity and continuity at the same time, the basic texture repair as shown in the figure below.

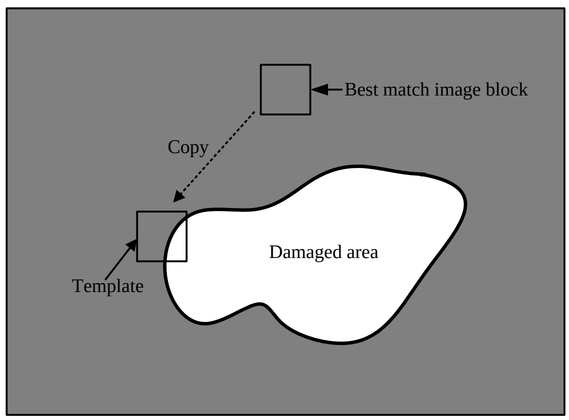

Figure 2: The basic texture repair

Commonly used method is to Criminisi algorithm, aiming at the best matching block in Criminisi algorithm search and populate the shortcomings, Hu put forward a kind of Criminisi algorithm combined with sparse representation, sparse representation method is used to replace Criminisi algorithm search the best matching patch, optimized the drawing marked area, increase the priority of credibility. The algorithm has strong anti-interference ability, and the coloring effect is obviously better than other algorithms, but the complexity of the algorithm still needs to be improved [Hu, Xiong and Iee (2017)]. To reduce the repair time, Ruzic et al. use texture descriptors to guide and utilize context information to accelerate the search for well-matched (candidate) patches, which could be used to improve the speed and performance of almost any (patch based) repair method [Ruzic and Pizurica (2015)]. Wei et al. proposed a new image restoration algorithm by combining PDE with texture restoration. This method can also reduce the repair time by classifying the known image texture and reducing the texture search area. However, like most traditional repair methods, it ignores the color information of the image even though the repair of image structure and texture information is taken into account [Yao, Sun, Zou, et al. (2010)].

To sum up, text-based image restoration algorithm can repair large damaged areas and has a good effect on some images. However, it is difficult to repair complex images, and it may even be impossible to find similar texture blocks. In addition, it takes a long time to search similar texture blocks around the damaged area, and the repair efficiency is not high.

2.3 Image restoration based on deep learning

Since CNN was proposed, there has been some important progress:

1) CNN can effectively extract abstract information of images in the convolution process.

2) Perceptual Loss enables a trained CNN network's feature extraction part to be an auxiliary tool of Perceptual Loss function in image generation.

3) GAN can use supervised learning to enhance the effect of network generation.

The emergence of generated antagonism network makes the research of image restoration technology reach a peak. At present, the loss function commonly used in image repair is the combination of confrontation loss and L2 loss. Calculation variance of L2 loss can stimulate the generation of network output, but the output result cannot capture high-frequency details and repair clear texture structure. Therefore, the introduction of confrontation loss can effectively solve the above problems. Counter losses are as follows:

$$\min_G \max_D V(D, G) = E_{x-P_{data}(x)}[\log D(x)] + E_{z-P_{data}(z)}[\log(1 - D(G(z)))] \tag{1}$$

The basic model of generating antagonism network applied to image restoration is shown in the following figure. The latest and effective image restoration model based on deep learning is developed on this basis. In 2016, Yang et al. used two CNN convolutional networks to train and repair images from two scales of texture and content. This method can repair high-resolution images through iteration, but it has defects in performance and memory [Yang, Lu, Lin et al. (2017)]. Deepak et al. attempted to use the generated confrontation network to achieve face image repair, and the combination of L2 loss and confrontation loss could achieve better repair effect. However, the region shape repaired by this method is fixed, which has strong limitations in practical application [Pathak, Krahenbuhl, Donahue, et al. (2016)]. In view of this problem, Liu et al. introduced local convolution, which can repair arbitrary non-central and irregular regions. However, this method still needs to create a mask based on the deep neural network and carry out pre-training for random lines [Liu, Reda, Shih, et al. (2018)]. Iizuka et al. used dilated convolutional layers to increase feelings of wild, trying to get a broader range of image information of no loss of additional information at the same time, also can fix any of the center and the effect of irregular region, but its repair effect is poorer for large structure of objects using the method. In order to improve the distorted structure or fuzzy texture of the reconstruction region boundary based on deep learning method [Iizuka, Simoserra and Ishikawa (2017)]. Yu et al. improved the generation network of image restoration on the basis of Iizuka's research, and decomposed the generation network into two networks: coarse network with reconstruction loss refers to training loss; refined network with reconstruction loss and GAN losses refers to training loss [Yu, Lin and Yang (2018)]. The expanded network structure extended the training time. In the same year, Yu proposed a new GAN loss, known as SN-PatchGAN, which applies spectral normalization discriminator to dense image patches to make the training fast and stable [Yu, Lin and Yang (2018)].

Generate against network based image restoration, however, sometimes the result of the repair still cannot get a fine texture, Yan and others in the U-Net framework introduced a special kind of shift-connection layer, namely the Shift-Net, it can with sharp structure and fine texture to fill the lack of any shape area, this method can effectively improve the effect of repair [Yan, Li, Li et al. (2018)]. In recent years, great breakthroughs have been made in the application of GAN to image restoration. In the future, there will still be more research progress in image restoration based on deep learning.

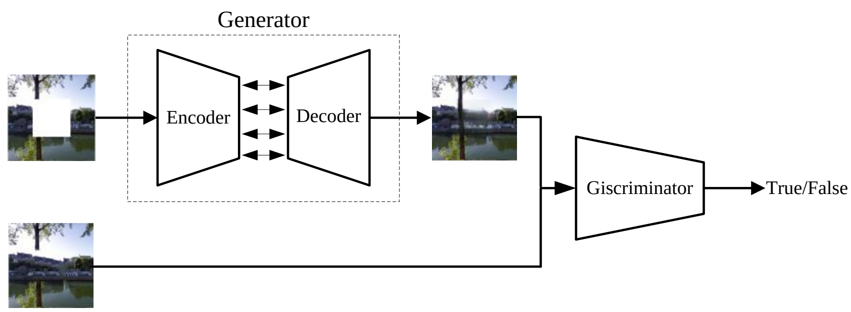

Figure 3: Image restoration model based on generation of antagonism network

3 Evaluation index

The evaluation methods of digital image restoration algorithm mainly include subjective evaluation and objective evaluation:

Subjective evaluation is generally judged by the observer based on the image evaluated. The quality of the repair effect depends on the visual judgment of the observer, that is, the repaired image is graded according to the predetermined evaluation scale or the observation experience of the observer. The results of the evaluation were obtained using the average score of a certain number of observers. Subjective evaluation mainly has two measurement scales: absolute scale and relative scale. As shown in the following table:

Table 1: Subjective evaluation criteria of image restoration

Level	Absolute scale	Relative scale
1	very poor	the worst in the picture
2	poor	worse than the average
3	general	average in the picture
4	good	better than the average
5	very good	the best in the picture

The objective evaluation method of image quality can be classified according to the required information level of the original image for reference. At present, there are three kinds of objective evaluation methods: the method based on mean variance, the method based on SNR and the method based on peak SNR.

The evaluation method based on mean square error evaluates the quality of image restoration by calculating the difference between the mean square value of the restored image and the original image. The calculation formula is as follows:

$$MSE = \frac{1}{M \times N} \sum_{0 \le i \le M} \sum_{0 \le j \le N} (i_{ij} - i'_{ij})^2 \tag{2}$$

The image in the above formula is the size of M*N pixels. Symbols i_{ij} and i'_{ij} represent the gray value of the original image and the restored image pixel, respectively.

The image quality evaluation method based on SNR is obtained by calculating the ratio of signal intensity variance to noise intensity variance. The mathematical formula is as follows:

$$SNR = 10 \times \log_{10} \left\{ \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} u(i, j)^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} \left[u(i, j) - u_0(i, j) \right]^2} \right\} \tag{3}$$

Image quality evaluation method based on peak signal-to-noise ratio between original image and image pixels after repair by calculation relative to the mean square error (2^n - 1)^2 for numerical evaluation of the quality of image restoration. The mathematical formula is as follows:

$$PSNR = 10 \times \log_{10} \left\{ \frac{255 \times 255}{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[u(i, j) - u_0(i, j) \right]^2} \right\} \tag{4}$$

In addition to judging the quality of restoration by the image restoration effect, the algorithm running time is another evaluation index. In the case of similar restoration effects, the less time it takes to repair, the better the image restoration quality.

4 Application

With the improvement of image and video visual requirements, digital image restoration plays an increasingly irreplaceable role in digital image processing.

Firstly, the development of digital image restoration technology can drive the development of other areas of image processing. Image restoration has a strong correlation with the basic problems involved in image restoration, image compression and image enhancement. The research on image restoration can promote the progress of the basic problems of image processing.

Image restoration is different from common image processing problems, such as image restoration, compression and enhancement. The idea of image restoration is to restore or reconstruct degraded images by some prior knowledge. Image enhancement is the processing of images for specific applications to make the visual effects better and more useful. Image compression is to reduce the amount of data needed to express the image information and reduce the redundant information of the original image. In other words, it is to restore the image with the least bit and the least distortion. These image processing techniques refer to the real information of the original image, while the pixel of the defect area is almost completely unknown in the image restoration technique, and the goal of restoration is usually to obtain the complete image based on the prior knowledge of human beings. In other words, image restoration is to analyze images according to the rules of human vision. The improvement of this technology mainly relies on the research of image model and human visual cognitive rules.

At the same time, digital image restoration technology is widely used in many other applications. Mainly includes:

(1) Image super-resolution analysis. Image super-resolution analysis (SR) refers to the algorithm used to reconstruct high-resolution images with low-resolution images as the template. Common methods are the methods of image interpolation, such as spline interpolation, zero order retention, bilinear interpolation, etc. However, due to the complexity of the image signal, the high frequency components of the original image cannot be restored by interpolating only one image. At this point, image restoration technology can be used to take the points under low resolution as the initial value under high resolution, and then combine with human vision rules to repair the remaining areas.

(2) Image coding and compression. At present, the structure of most image compression algorithms is transformation plus entropy coding. The transformation mainly includes discrete cosine transform, fractal transform, wavelet transform, etc. The restoration technique can only encode part of the image information when the image is compressed, while the rest of the image can be reconstructed by the restoration method. This method makes use of human visual redundancy and can improve the coding efficiency and image quality [Wu, Zhang, Sun et al. (2009)].

(3) Error hiding in image and video transmission. Video is prone to packet loss during transmission [Shibata, Iiyama, Hashimoto et al. (2017)]. Image repair technology is used to process blocks with errors received. Video quality can be improved without changing transmission bandwidth and communication protocol, and secret messages can be embedded in video [Nie, Xu, Feng et al. (2018)].

(4) Expand the view and virtual scene construction. Panoramic splicing with image fusion technology can expand the view of image browsing, extend the image from the boundary by image restoration technology, carry out image roaming, and edit online references of the Internet and large image database through scene restoration.

(5) Image steganography. The secret image first generates normal and independent images with different meanings from the secret image. The generated image is then sent to the receiver and fed to the generated model database to generate another image that is visually the same as the secret image. This method has high capacity, security and reliability [Duan, Song, Qin et al. (2018)].

The maturity of image restoration technology also brings another problem: realistic computer-generated graphics can be forged into photographic images, which leads to serious security problems. The use of deep neural network can effectively detect photographic images and computer-generated graphics [Cui, McIntosh and Sun (2018)].

5 Conclusion

Since 2000, the concept of image restoration has been proposed, from the traditional non-text-based image restoration technology and text-based image restoration technology to the current deep learning-based image restoration technology. At present, the digital image restoration technology has made some achievements in the theory and practical application, but it still has some deficiencies and needs to be further improved. Even though the application of deep learning makes the image restoration without PS traces, it is still a big difficulty in the acquisition of the image restoration area. The algorithm itself cannot automatically acquire the area that needs to be repaired.

In addition, although deep learning can solve some problems in traditional image restoration techniques, it is urgent to improve training speed. Finally, the digital image technology to repair the success will not only greatly broaden the application field of image repair technology, and because in these application fields of research and development at the same time, will give feedback from these applications in the field of new problems, which will further enrich the content of the digital image restoration technology and promote the development of it.

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