ISSN: 2664-9640

Research on Image Repair Based on DCGAN

Jinfan Huang[1,*] , Rong Li[2]

[1]School of Computer Science, Yangtze university, Jingzhou 434020, China;

[2]School of Health Science Center, Yangtze university, Jingzhou 434020, China.

* Corresponding Author

Abstract

With the rise of deep learning and the generation of image large data sets, people begin to try to apply deep learning methods to the study and application of images, and image repair has gradually become a hotspot of application. Traditional image restoration generally adopts PS tool for perceptual restoration of images. Although this method has a high restoration rate to a certain extent, it has problems of complex restoration process and long restoration time. In this paper, DCGAN is used to study image restoration based on image semantics. First input complete pictures constantly training to get a realistic fake images generated network model, the second input random distribution, lack of sense of loss and the edge of the part information, continuously optimize the input distribution to achieve the objective of the approximation image missing distribution, finally put the distribution into the generator to generate the best fake pictures to fill the missing parts, in order to achieve the goal of image restoration.

Keywords

Deep-learning, Image-inpainting, DCGAN, Generated-fake-picture, Edge-information.

1. Introduction

Image repair is the process of using complex algorithms to reconstruct the lost or damaged parts of a graph, whose purpose is to automatically recover the lost content according to the known content in the image, with a wide range of applications[1].Since the image repair methods are widely studied, they can be divided into partial differential and variational methods, sample-based image repair methods.Deep learning-based repair methods are an emerging class of methods proposed in recent years.Partial differential and variational-based methods can achieve good repair results in small-size damaged image repair; sample-based methods can achieve relatively good results in large-area damaged image repair.Deep learning-based repair method by stacked deep neural network containing a large number of hidden layers of deep training learning can be trained through massive data of nonlinear complex relationship mapping between samples, this is the image repair based on image content of semantic repair expected to solve the problem, in a large area of image repair can sometimes achieve very amazing results.

2. Application of Deep Learning in image repair

With the breakthrough progress of deep learning theory in the field of computer vision, more and more scholars begin to constantly improve the deep learning algorithms about image repair[2].The following is a brief introduction of the following current mainstream models of deep learning in image repair.

ISSN: 2664-9640

2.1. CNN works with image repair

The application of CNN to image repair is mainly combined with the autoencoder, input the defect image, and then use the context information for convolutional autoencoder training, and finally output the repair map for the damaged part.Initially, Pathak et al. proposed an image repair networkcalled Context Encoder[3] , which is trained with Euclidean distance and adversarial loss as constraints, but the generated images will generally be blurred without accurate information.Therefore, the local adversarial loss is added as a constraint. By judging whether the repair graph or the fake image is generated from the original image or the generator, the output result has more edges and the structure is more reasonable.But this constraint only determines the authenticity of the repair area, and cannot regularize the global structure of the repair image; and it can hardly have a direct impact on the repair area accident during backpropagation, making the pixel value of the repair area boundary not continuous.In order to solve this problem, Li and others joined the global against loss, will repair area completion to the original image, the repair image authenticity, judge this is splicing out of the figure or the original picture, if very sure is considered not the original picture then need to adjust the generator.

Convolutional autoencoder mainly contains two encoders, both input the image to be repaired. The difference is to output the repair figure of the missing small piece, and compare the repair map with the original figure of the missing small block to generate the local confrontation loss; the other encoder is the output of the repaired complete figure and the original figure for the global confrontation loss, trying to make the sum of the two losses is the minimum of convolutional autoencoder training target.The following is a network structure diagram with increased local adversarial loss and global adversarial loss. The fixed graph input encoding-decoding network generates the patch block, and then updates the patch block and the original missing block and the complete original image:

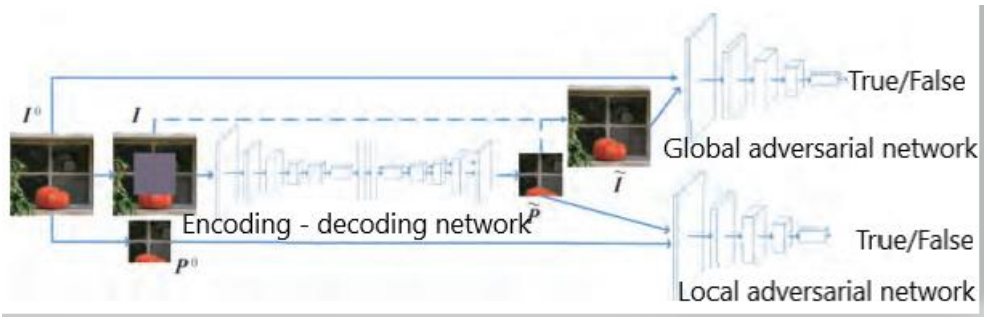


Figure 1: A diagram of local and global adversarial loss

2.2. GAN, together with the image repair

The GAN network mainly includes a generator G and a discriminator D, which play games with each other and finally reach the Nash equilibrium.When it is applied to image repair, the complete original image network is first used to train the image generation model, randomly input some noise, using the generator of the GAN model to game each other, so that the generator can have the ability to produce fake pictures close to the original image[4]. But the model is not enough to generate the best fake image repair, because the false image input probability distribution is not necessarily consistent with the probability distribution of repair image, so the fake image input noise iterative update, until the training input probability distribution and to repair image, can be extracted by the generator and damaged the original image size of damaged block, using damaged block and to repair the simple channel splicing can complete the image repair.

2.3. DCGAN, together with the image repair

Traditional GAN-based image repair methods have problems such as unstable training and easy convergence, so Radford et al. proposed deep convolution generation adversarial network DCGAN, which combines the construction process of CNN network and GAN network [5]. The appropriate fix error penalty is set, so that the generator improves the ability to produce fake images close to the original image, while the discriminator improves the ability to distinguish the original image and generate images.Ideally, for the two trained networks, for the generated network, the probability distribution of the input damaged image and then the output repair image is consistent with the original image.Then simple cutting and splicing can be done to the original image, to achieve more effective image repair.This part of the principle is mostly similar to the repair principles of GAN networks.

2.4. Comparison of advantages and disadvantages

Experiments have proved that CNN, GAN and DCGAN can all be used for image repair, but all have some advantages and disadvantages, see Table 1.

Table 1 :Comparison of CNN, GAN and DCGAN for image repair

Fix image methods	advantages	disadvantages
Convolutional autoencoder	Any broken area of the image can be repaired	Only low-resolution repair images can be generated; image repair is not ineffective
Using the GAN network	High-resolution repaired images can be generated; GAN is more representative than features learned by CNN	High-resolution repaired images can be generated; GAN is more representative than features learned by CNN;The generation optimization of G comes from the feedback of the resolution result of D. If the resolution result of D is too good, the gradient of G will disappear; if the effect of G generating false pictures is too good, D will not distinguish the true and false pictures, resulting in the mode collapse.
Using the DCGAN network	Combining the advantages of CNN and GAN, reducing the instability of GAN network training	Although the instability of GAN training has-reduced, there will be instability

3. Construction of the image generation repair model

3.1. Construction of the generative model

The hidden layer of the discriminator model consists of four convolutional layers.Take a single picture as an example, the four convolution layers all use a 5 * 5 convolution step of 2 filter, all are standardized and unified after the convolution, using relu as the activation function, output by double the reduced image and increase the number of channels [6].The construction

ISSN: 2664-9640

discriminator actually operates four times to reduce the image by sixteen times and increase the number of output channels. Finally, the output layer is first pulled into a one-dimensional vector with one leveling operation, and then makes the output to 1 * 1 with the full connection layer, and activated with the sigmoid function.

The hidden layer of the generator model consists of four transposed convolution layers. Taking a single picture as an example, the first layer uses the full connection layer to change 100-dimensional input noise into an image matrix with output dimension 8192 * 1, and then changes the image matrix to 4 * 4 * 512. After reshape, the four layers of transposition convolution layers use filters with convolution step 2, which are unified after the transposed convolution, using LeakyReLU as the activation function.The neural layer performing the above actually output the twice-larger image and the reduced number of channels.The build generator actually performs the above operation three times, increasing the image by eight times, and the number of output channels is constantly reduced, and finally the output layer uses the tanh function activation to ensure that the input is in [-1,1].

The model structure diagram is shown in Figure 2 below:

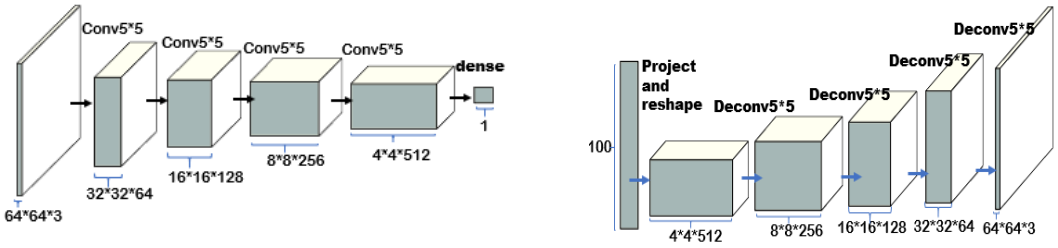


Figure 2:Model structure diagram of the discriminator and generator

3.2. Construction of the repair model

In theory, the best fake image generated from the generative network is the unbroken original image.In fact, this effect is hardly achieved.Not only that, but the images from the Internet often change in the unbroken areas of the broken image, even if they are much like the original image.Therefore, further image repair treatment is needed to ensure that the last generated repair map does not change in the unbroken area of the damaged map.

The principle of image repair is: first, input random noise, random noise can generate the best fake pictures through the image generation model.First, obtain the damaged area of the damaged picture, extract the relevant area corresponding to the fake picture, and then use the fake picture to repair the missing part of the original image. In other words, the missing part of the original image uses the projection of the fake image to replace the missing part of the original image.The schematic diagram is shown in Figure 3 below:

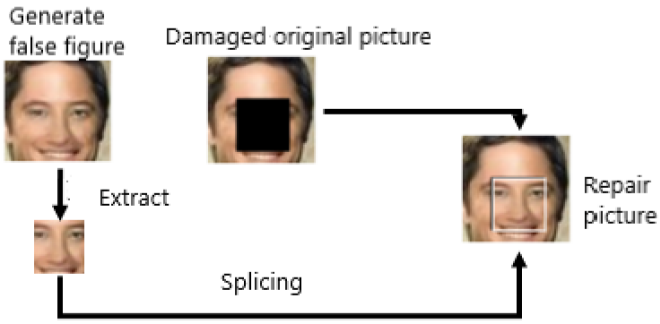


Figure 3: Schematic diagram of the image repair

ISSN: 2664-9640

In order to obtain the projection of the damaged part of the original image in the fake image, it is necessary to process the image with a mask to block the specific part of the image.The mask matrix is a matrix containing only 0 and 1, and the graph matrix is retained as is for positions of the mask matrix of 1 and is not shown for positions of 0 of the mask matrix.Extract the size of the picture and generate a mask matrix of the same size. Set 0 or 1 according to the damaged part, and extract the damaged corresponding part of the fake picture, put the damaged part into 1.Considering that it is impossible to get a large number of images with similar broken condition training sets, so a large number of similar layout images are cut in a specific area to generate the same missing condition images.Repair formula (LC represents the repair figure, G (z (i)) represents the generated fake picture,χrepresents the original image, and MASK represents the trimmed part):

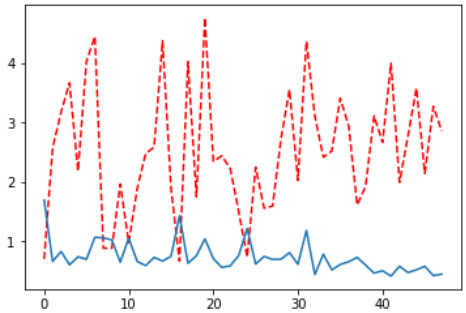
$$Lc = G\left(z^{(i)}\right) * MASK + (1 - MASK) * x \tag{1}$$

The construction of the image repair model can be added to the original image generation model.In training, should be first before image repair iterative training image generation model, to find the weight matrix can generate false image, and then use the weight matrix for image repair model iterative optimization, specifically complete image generation iteration, and then stop image generation optimization, the image generation input noise iterative optimization, find the same input distribution after generating the best false image, extracted to false image projection splicing is complete image repair[7].

4. Experimental Result

The CelebA face dataset, which contains 202,599 face images of 10,177 celebrity identities, and has five face marks: the left and right of the eye, the nose, and the left and right of the mouth.The data file img_align_celeba.zip for this experiment is the picture of all face images in CelebA in the center and of equal size.3000 images were selected as the training set, all using Tensorflow 2.6 deep learning open source framework and CPU configured as Intel Core With the i7-12700F, the GPU is configured as a NVIDIA GeForce RTX 3060 12G video memory, and the present model is trained on a PC platform with Win 10 + 16G memory. Using Adam as the optimizer, the learning rate was 0.0002, and the training was stopped after 1,000 epoch of the iteration.The experimental results are as follows:

Generation model: Although using a discriminator iteration, a generator iteration can achieve the purpose of image generation (red is the generator generation loss, blue is the discriminator discriminant loss), but it is found that the discriminant discriminant loss tends to zero, that is, the gradient disappears.Therefore, the image generation model is improved, and one generator loss is increased on the original basis, that is, the optimized model becomes one discriminator optimization iteration and two generator iterations.The above is the original generation process, and the following is the optimized image generation results. The comparison effect of the two is shown in Figure 4 below:



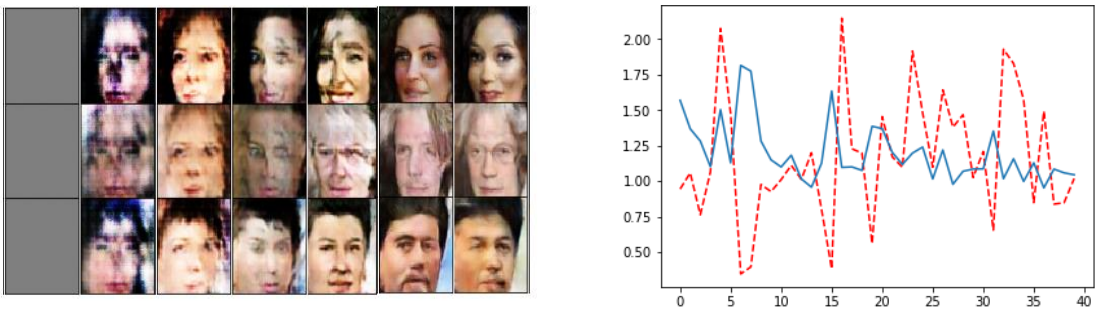
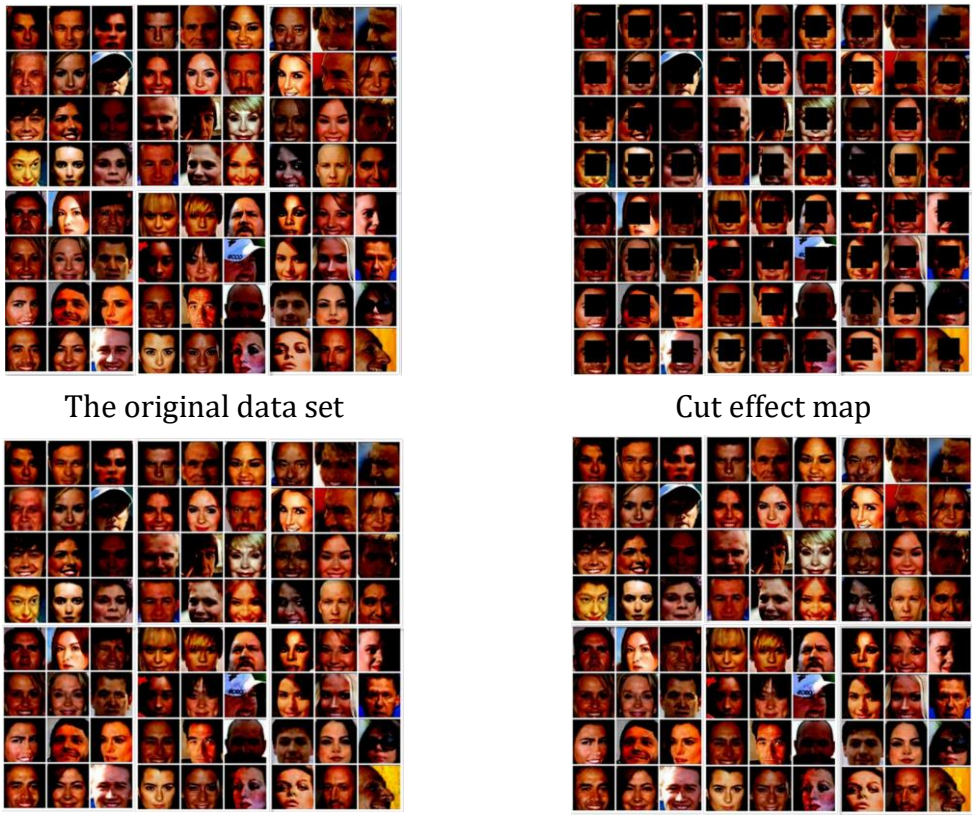


Figure 4: Image generation Process Comparison result figure

The image repair results are as shown in Figure 5 below:



The original data set

Cut effect map

The resulting false picture

Repair effect

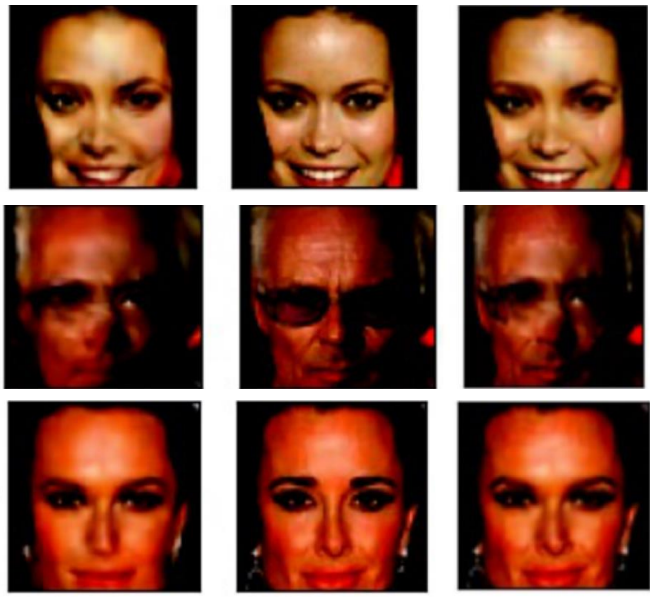
Figure 5:Image repair effect display

In the experiment, 605 images were used to repair 605 pictures, and the repair effect of human eye senses was judged as shown in Table 2:

Table 2:Repair Results Judgment table

criterion for judgement	Numerical / proportional
Fix the image that looks like a human being	603/99%
Can find out the traces of repair	376/62%
Can't see if the image or the original	442/73%
It is obvious to fix the image	74/12%

To highlight the comparative repair effect, the typical repair cases are displayed, as shown in Figure 6 below:



There are signs of splicing

Test the stability, the effect is not very ideal

Good results, but an abnormal nose tilt

Figure 6 :Typical repair case display (best fake picture, original picture, repair picture from left to right)

5. Conclusion

The repair effect of this method has been particularly considerable for most clear positive face images, but there are also changes outside the damaged area, and the repair effect of large area defects and high resolution also needs to be improved, and there is a big gap with professional prosthetics.In addition, the current image repair technology based on deep learning is mainly automatic repair, in some complex scene image repair, through some human-computer interaction or using the same designated image guidance repair strategy is also worth studying, so as to further promote its practical application, rich digital image repair technology.

References

[1] Bertalmio M, Sapiro G, Caselles V,et al. Image inpainting［C］ / /Proceedings of the 27th Annual Conference on Computer Graphics and Interactive Techniques.New York,USA: ACM,2000: 417-424. ［DOI: 10.1145 /344779.344972］

[2] Z.W. Qiang , L.B. He , X. Chen , et al: Summary of image repair methods for Deep learning, Chinese Journal of Image Graphics(2019),24 (03): 447-463.

[3] Pathak D, Krhenbühl P, Donahue J, et al.Context encoders:feature learning by inpainting [C]//Proceedings of 2016 IEEEConference on Computer Vision and Pattern Recognition.Las Vegas, NV, USA:IEEE, 2016:2536-2544.[DOI:10.1109/CVPR.2016.278]

[4] J. Li: *Research on Image Repair Techniques Based on Generative Adversarial Networks* (MS., Southwestern Jiaotong University, China 2019).

[5] Y.J. Cao , L.L. Jia , Y.X. Chen , et al: Review of Generative Adversarial Network and its Computer vision applications , Chinese Journal of Image and graphics(2018),23 (10): 1433-1449.

[6] Y. Ma：*Research on Face Image Repair Algorithm Based on Deep Generative Model* (MS., Xidian University, China 2019).

[7] T.C. Li , J. He ： An image repair algorithm based on a generative adversarial network, Computer Application and Software,(2019),36 (12): 195-200 + 267.