Restoration of non-structural damaged murals in Shenzhen Bao’an based on a generator–discriminator network

Jiao Li\textsuperscript{a}, Zhiqin Deng\textsuperscript{b}, Mingtao Pan\textsuperscript{c}, Honghai Chen \textsuperscript{a,*}

**Affiliation**
\textsuperscript{a} School of Cultural Heritage, Northwest University, Xi’an, 710069, China.
\textsuperscript{b} Guangdong Provincial Research Center for Artificial Intelligence and Digital Orthopedic Technology, Hand and Foot Surgery Department, Shenzhen Second People’s Hospital/the First Affiliated Hospital of Shenzhen University Health Science Center, Shenzhen 518000, China.
\textsuperscript{c} The Department of History, Sun Yat-sen University, Guangzhou, 510275, China.

\textsuperscript{*} **Corresponding authors:**
Honghai Chen, School of Cultural Heritage, Northwest University, Xi’an, 710069, China, Tel.: +86-13032900457, E-mail: chen82164@163.com.

**Disclosure of potential conflicts of interest:** There are no potential conflicts of interest.

This manuscript has been thoroughly edited by a native English speaker from LetPub (www.letpub.com). Editing Certificate was provided upon request.
Abstract:

It has been 40 years since the reform and opening up of Shenzhen. However, there are many ancient murals hidden in the modern city. Murals are important resources that allow us to explore local history and culture. In order to better preserve and restore ancient murals, we propose a generator–discriminator network model based on an artificial intelligence algorithm. For non-structural damaged murals, the generator network method in deep learning can automatically generate the missing parts of a mural that are similar to salt-and-pepper noise. The generated image is sent to the discriminator network, which is used to determine whether the input image was generated through the generator network or was a real image. When the discriminator has significant difficulty distinguishing between the real image and the image generated by the generator network, it can be considered that the image has been well repaired by the generator network. Based on the available data, 137 mural images were selected for model training, and 22 mural images were used to observe the restoration effect of the real mural after model training. From the experimental results, the proposed algorithm has a good repair effect on the point-like damaged murals, but has a poor repair effect on murals with serious structural damage. This latter finding is due to the limited research data. Nonetheless, the algorithm can still guide restoration workers in mural repair.

Keywords: Mural restoration; Mural in Bao'an District; Generator network; Discriminator network;
Introduction

According to archaeological materials, Bao'an District has a history of more than 7,000 years of human activity and a history of more than 1,600 years of county construction. With a long history, Bao'an is the "root of Shenzhen–Hong Kong culture"[1]. Its aborigines include Cantonese and Hakka people, and the architecture has characteristics of the Lingnan region culture [2, 3]. Ancestral halls, temples, study rooms, and old-style private schools of Cantonese dwellings, along with the walled-houses and watchtowers of Hakka dwellings, are the most distinctive. Integrating architectural art, sculpture art, painting art, philosophy, ethics, geomancy, calligraphy, folklore, and other cultural elements, these buildings are precious local historical and cultural resources. Moreover, these buildings are considered the local "original ecological museum of architectural culture"[4]. In these buildings, the outer eaves, the bottom of the inner beam, ambulatory, alcoves, lintel (of a door), and other places are distributed with unique murals. Many ancient murals have been damaged to varying degrees due to the natural environment and man-made damage. Although some scholars have put forward some suggestions on the preservation and restoration of murals [5, 6], the restoration of murals is still urgent.

At present, the restoration of murals mainly relies on the good painting techniques and rich experience of scientific researchers, which takes a long time and produces uneven effects. Artificial intelligence technology is currently experiencing tremendous development and innovation. In the field of digital image repair, powerful autonomous learning and thinking algorithms such as deep learning and neural
networks have been proposed. The application of these algorithms can help restoration workers complete the restoration of murals and other cultural relics efficiently and accurately.

Based on this, we take the conservation and restoration of Bao'an District murals as an example and employ a generator–discriminator network algorithm (a type of neural network algorithm). Using 137 relatively intact murals as training models and 22 poorly preserved murals as restoration objects, the AI technique was used to restore images of ancient Bao'an District murals.

Methods

Generator–Discriminator network algorithm

A generator–discriminator network model is used in this paper. The generator network is based on the improved U-NET model [7]. The generator is essentially an auto-encoder that is subdivided into an encoder and a decoder. The encoder is composed of a multi-layer lower sampler and the decoder of a multi-layer upper sampler. The repaired image of the mural is generated by the generator.

Subsequently, the repaired image is sent to the discriminator network. The discriminator network is used to determine whether the input image is generated by the generator. When the discriminator has significant difficulty distinguishing between the real image and the image generated by the generator network, it can be considered that the image has been well repaired by the generator network. For murals with non-structural damage, the loss-point distribution is similar to salt-and-pepper noise (Fig. 1). In this paper, pepper and salt-and-pepper noise algorithms for removing
black spots are adopted to simulate the loss of murals (Fig. 2).

The overall repair process is as follows: the damaged mural image is put through the generator network to obtain the repaired image. After the repaired image and the damaged image are stitched together, they are input to the discriminator network, which determines whether the input image is generated for the model or captured for the real image (Fig. 3).

**Generator network structure**

The generator network is based on a modified version of the U-Net model, which consists of an encoder and a decoder. The encoder and decoder are connected directly through the residual network (Fig. 4).

**Encoder**

The encoder consists of eight coding units, each of which is a Conv -> Batchnorm -> Leaky ReLU structure. The fixed stride of each layer of convolutional network is equal to 2, which is used for down-sampled images. The input of each layer will be retained for residual connection to retain more image details. The image array is batch_size, 256, 256, 3 (Table 1).

**Decoder**

The decoder consists of 8 decoding units, which can be analogized as the reverse process of the encoder. Each decoding unit is a TransposedConv ->Batchnorm-> ReLU structure and is used for image reconstruction. By connecting the encoder network with residuals as input, a dropout layer is added in the first three layers of the decoder to enhance robustness. Detailed figures are shown in Table 2.
**Discriminator network structure**

The discriminator network is also an image convolution network. The network structure is similar to the classic image classification network [8]. The difference is that the input of the classical image classification network is a picture while the output is a classification of the picture. In this paper, the discriminator network input is composed of two pictures, and the output is a 30 x 30 matrix. Each element represents the classification result (0 or 1) of its region. For the scenario in this article, 0 indicates that the discriminator network considers this region to be a restored mural picture generated by the machine learning model, and 1 represents that the discriminator network considers this region to be a real mural picture. By subdividing the spliced image into areas of 30 x 30 and highlighting these losses as needed in the loss function, we can improve the degree of detail in the images generated by the generator and achieve more satisfactory results (Fig. 5).

In terms of specific structure, this article first uses a 3-layer encoder unit to down-sample the 256 x 256 x 3 image to 32 x 32 x 256. Then, we connect a layer of ZeroPadding2D to expand the image to 34 x 34 x 256, and pass the Conv2D layer, down-sample to 31 x 31 x 256, perform batch normalization, and repeat all of the above steps. Finally, we obtain a 30 x 30 x 1 matrix.

**Loss function**

**Generator network loss function**

The following two indices can be used to measure the effect of the generator network: (1) the spoofing effect of the generator network for the discriminator
network, and (2) the difference between the repaired image and the actual image.

For (1), Log Loss is used in this paper to calculate the loss between the discriminator network’s output and the 30 x 30 all-1 matrix.

\[ L_{Gen1} = \log loss(\text{ones}, \text{discriminator}_{\text{gen}}_{\text{output}}) \]

Here, \text{ones} comprise a 30 x 30 matrix (all of the elements are 1), and \text{discriminator}_{\text{gen}}_{\text{output}} is the output of the repaired image that is generated by the generator network inputted to the discriminator network.

For (2), this paper first calculates the absolute value of the difference between the real image matrix and the generated image matrix, takes the average value of the row to obtain a 30 x 1 matrix, and then takes the average value of all columns (namely the reduce_mean algorithm, which is the three-step process just described). The final output is used as the loss function.

\[ L_{Gen2} = \text{reduce}\_\text{mean}(|\text{real}\_\text{image} \ - \ \text{gen}\_\text{output}|) \]

Here, \text{real}\_\text{image} is the matrix of the real shooting image, and \text{gen}\_\text{output} is the matrix of the repaired image generated by the generator network.

The total generator network loss function can be expressed as follows:

\[ L_{Gen} = L_{Gen1} + \lambda L_{Gen2}. \]

In order to keep the ratio of \( L_{Gen1} \) to \( L_{Gen2} \) in a reasonable range, the article adds \( \lambda \) as an adjustment. Hence, \( \lambda \) controls the effect of the discriminator network on the generator network. The value of \( \lambda \) is 90.

**Discriminator network loss function**

The following two indicators can be used to measure the effect of the
discriminator network: (1) the identification effect of the discriminator network on the real shooting mural image, (2) the identification effect of the discriminator network on the repaired image generated by the generator network.

For (1), this paper uses Log Loss to calculate the loss between the output of the discriminator network and the 30 x 30 all-1 matrix when the input is a real mural image.

\[ L_{Dis1} = \log \text{loss} (\text{ones}, \text{discriminator}_\text{real}_\text{output}) \]

Here, \text{ones} comprise a 30 x 30 matrix (all of the elements are 1), and \text{discriminator}_\text{real}_\text{output} is the output that is input to the discriminator network after stitching together the real mural images and damaged images.

For (2), Log Loss is used in this paper to calculate the loss between the output of the discriminator network and the 30 x 30 all-0 matrix when the input is used to generate images for the model.

\[ L_{Dis2} = \log \text{loss}(\text{zeros}, \text{discriminator}_\text{gen}_\text{output}) \]

Here, \text{zeros} comprise a 30 x 30 matrix (all the elements are 0), and \text{discriminator}_\text{real}_\text{output} is the output that is input to the discriminator network after stitching together the mural repaired images and damaged images generated by the generator network.

The total discriminator network loss function can be expressed as follows:

\[ L_{Dis} = L_{Dis1} + L_{Dis2}. \]

Results and Discussion
The mural image analyzed

According to incomplete statistics, more than 1,000 architectural murals are well preserved in Bao'an. These murals can be divided into four categories according to the painting’s theme: landscape, character stories, flowers, birds, or animals, and calligraphy. These murals are the epitome of Lingnan folk life and traditional culture, the carrier of typical local culture, and the precipitation of Bao’an people's thoughts and culture. They play an indispensable role in the study of Lingnan culture and have important cultural and artistic value. The 137 murals used as training models and the 22 murals utilized as restoration objects are typical representatives of the murals in Bao'an District, and the study on mural restoration using them as basic image data is representative to a certain level (Fig. 6).

From the perspective of regional distribution, 159 murals used in the experiment came from 15 ancient villages in 7 subdistricts of Bao'an District. As can be seen from Table 1, the specific distribution covers most of Bao'an (Fig. 7) and is widely distributed, representing the overall appearance of the murals in the district.

In terms of architectural type, there are 32 murals in watchtowers, accounting for 20.13%, 9 murals in old-style private schools (5.66%), 21 murals in residences (13.21%), 6 murals in study rooms (3.77%), 35 murals in temples (22.01%), and 56 murals in ancestral halls (35.22%). These architectural types cover the typical architecture of the Cantonese and Hakka people, and are representatives of Lingnan culture.

Judging by the dates inscribed on the murals, most of the buildings were built in
the Ming and Qing dynasties up to the Republic of China. Note that the painting date of 7 murals is to be determined. According to the inscribed dates, 38 murals were produced before 1840, and 114 were produced between 1840 and 1949. One of the largest, oldest, most valuable, and best preserved murals found in Shenzhen and even Lingnan is in Maoshan Public Family School located in Fuyong Fenghuang Ancient Village. There is a painting of the Eight Immortals (Fig. 8) on the wall of the front hall; it was painted in 1819. In terms of time, the murals in Bao'an District were only painted on a large scale more than 200 years ago, but they are the condensation of the folk culture in Lingnan.

Regarding the content of murals, there are 107 murals of flowers, birds and animals, accounting for 67.30% of all murals, 27 murals of character stories, accounting for 16.98%, and 25 murals of landscapes, accounting for 15.72%. In addition to traditional themes, the murals found in Bao'an include foreign buildings, roads, cars, and ships of the late Qing Dynasty and the Republic of China period. Such murals showcase the historical features of the economic and cultural exchanges between Lingnan and overseas countries. An example is the Wharf and Foreign Firm in the Ancestral hall of Zhao family in Shangpai Village, Shiyan Street (Fig. 9).

**Influence of discriminator network resolution on repair effect**

We use 256 x 256 images as input, and a matrix with a discriminator network output resolution of 30 x 30. In order to explore the impact of the discriminator network resolution on the quality of the repaired image, this paper selected several different resolutions for experiments. The following results are the outputs of the
model after 150 rounds of training. From left to right in Fig. 10, the final output formats of the discriminator network are 2 x 2, 6 x 6, 30 x 30, and 126 x 126. The pictures have not been compressed and can be enlarged for better viewing.

In order to facilitate observation, this article selects two groups of pictures from the 2 x 2 image group and the 126 x 126 image group for comparison (Fig. 11). It can be seen that due to the higher resolution of the 126 x 126 group, more details are restored on the face of the person. Upon zooming in and observing carefully, we can see that the edges of the branches are sharper. However, at the same time, if we compare the leaves, it can be seen that the black noise generated by the 126 x 126 group is significantly more than that of the 2 x 2 group. This is in line with expectations.

**Restoration effect of the discriminator network used for real mural images**

In order to test the restoration effect of the algorithm proposed in this paper on real, non-simulated loss murals, we selected 22 mural images with which to observe the restoration effect of the real mural after model training. The 22 mural images are disperse and dot-like, and similar to simulated damaged murals for repair experiments.

As shown in Figure 12, this article also uses 22 images of 256 x 256 as input for experiments (only 4 of them are shown in the article). The left side of Figure 12 represents the original image to be repaired, and the right side represents the image repaired using this algorithm. It can be seen from the figure that this algorithm has a good repair effect for disperse and dot-like damaged murals (Fig. 12, lines 1–3).
Meanwhile, while for severely structurally damaged murals, it has a poor repair effect (Fig. 12, line 4).

**Discussion**

In recent years, many scholars have paid attention to the use of some technical methods for the protection and restoration of murals. Using technology to study the influence of *Streptomyces* on the color of ancient Egyptian tomb murals, some solutions have been presented [9]. The digital simulation restoration of ancient Chinese murals has mostly involved the study of Dunhuang murals [10], and there are few studies on the restoration of precious murals in other places, such as the ancient murals in Shenzhen. For example, a digital image restoration technique with a macro perspective was constructed for the Dunhuang mural protection and restoration system architecture. There are some other improved image decomposition techniques, such as the Criminisi algorithm and Markov algorithm for the digital repair of Dunhuang murals [11, 12]. Some algorithms are digital restoration methods based on the classification of mural destruction patterns or plaque characteristics. For example, morphological component analysis (MCA) has been used to decompose a mural into two parts, the structure and texture, to repair cracks and mud spots in the mural, respectively [13, 14]. Some studies have pointed out a mural restoration method based on sample block priority can accurately calibrate the mud spot disease in Tibetan digital murals and perform simulated restoration [15]. The intelligent restoration of ancient murals described above has achieved certain results. Nevertheless, mural restoration using artificial intelligence is still in its infancy.
Generally, traditional image repair methods according to the repaired area are divided into (1) small damaged areas that are transferred to known areas for repair [16-19], and (2) large damaged areas that are synthesized and matched for repair [20, 21]. In practical application, the calculation is very large and time-consuming. Moreover, in the field of mural image restoration, due to the small number of preserved complete murals, the traditional method uses some ordinary pictures as training input [20]. Although the problem of sample size is compensated for, the trained model is often not effective for actual repair because the artistic style is not considered in the process of transfer learning [22]. In this paper, 137 murals were used for training and learning how to restore the murals, not for restoring the actual ones directly. Through the generator and discriminator network proposed in this paper, the use of the 137 murals as training models can result in better repair of the real murals.

**Conclusion**

For the mural images that have experienced severe wear and tear but have not lost structural information, the proposed method can restore the mural images with good results by employing a generator–discriminator network. As the resolution of the discriminator network improves, the image generated by the model obtains more details, and some noise is also introduced. In the actual use process, it is necessary to select an appropriate value to achieve a balance between detail and noise. This method can also be used to try to repair structurally damaged murals. However, due to limited research materials, this article has not yet attempted such repair work.
Abbreviations
Conv: Convolution layer; Batchnorm: Batch normalization layer; ReLU: Rectified Linear Unit.

Acknowledgements
The authors wish to express their great gratitude to the Researchers Weiwen Huang and Dr. Jinming Liu at the China Mobile Guangdong Co for their kind support and assistance with this research.

Besides, we thank LetPub (www.letpub.com) for its linguistic assistance during the preparation of this manuscript.

Authors’ contributions
All the authors contributed to the current work. JL devised the study plan and wrote the manuscript. ZQD, JL and MTP were responsible for the whole experiment, data collection and analysis. HHC supervised the entire process and provided constructive advice. All authors read and approved the final manuscript.

Funding
This study was funded by The National Social Science Fund of China (2019), grant number: 19BZS117.

Availability of data and materials
All data for analysis in this study are included within the article.

Competing interests
The authors declare that they have no competing interests.

References
1. X. Hu, Bao'an: From the root of Shenzhen-Hong Kong culture to the core of the Bay Area, Shenzhen Daily, Shenzhen Press Group, Shenzhen, 2019, p. A08.
2. Y. Lai, Research on Ancestral Halls of Guangfu Clan in Pearl River Delta (in China), South China University of Technology, Guangzhou, 2010, pp. 18-30.
3. C. Wu: An Investigation on “Guihutanglaowei” of Guanlan in Shenzhen——Concurrently Discussing the Reform of the Hakka Chen Clan to the Local Baoan-type Folk Residence (in
4. R. Culture, Television, Tourism and Sports Bureau of Bao an District, Decorative Art of Historic Buildings in Baoan-Mural (in China), Zhongzhou Ancient Books Publishing House, Zhengzhou, 2015.

5. L. Liu, Research on Shenzhen Phoenix Village Protective Update Strategy Based on Symbiosis Theory (in China), Harbin Institute of Technology, Harbin, 2014, pp. 2-10.

6. J. Song, Study on Regionally for Contemporary Museum Design in Pearl River Delta Region (in China), South China University of Technology, Guangzhou, 2012, pp. 68-90.

7. O. Ronneberger, P. Fischer, T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015.

8. J. Long, E. Shelhamer, T. Darrell: Fully Convolutional Networks for Semantic Segmentation. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2015; 39 (4): 640-651.

9. E.S.F. Abdel-Haliem: Discoloration of Ancient Egyptian Mural Paintings by Streptomyces Strains and Methods of Its Removal. International Journal of Conservation Science, 2012; Volume 3 (Issue 4): 249-258.

10. Y.H. Pan, L.U. Dong-Ming: Digital Protection and Restoration of Dunhuang Mural. Acta Simulata Systematica Sinica, 2003.

11. X.-P. Yang, S.-W. Wang: Dunhuang Mural Inpainting in Intricate Disrepaired Region Based on Improvement of Priority Algorithm (in China). J Comput Aided Des Comput Graph, 2011; 23 (2): 284-289.

12. YANG, Xiao-ping, WANG, et al.: Dunhuang mural inpainting based on Markov random field sampling. Journal of Computer Applications, 2010.

13. J. Shen, H. Wang, W.U. Meng, et al.: Tang Dynasty Tomb Murals Inpainting Algorithm of MCA Decomposition. Journal of Frontiers of Computer Science & Technology, 2017; (11): 1826–36.

14. L.N. Smith, M. Elad: Improving Dictionary Learning: Multiple Dictionary Updates and Coefficient Reuse. IEEE Signal Processing Letters, 2013; 20 (1): 79-82.

15. Z.G. Jiang J, Wang ZX: Digital curtain diameter mould disease auto calibration and restoration method simulation. Comput Simul, 2018; (35): 215-219.
16. J. Shen, T.F. Chan: Mathematical Models for Local Nontexture Inpaintings. Siam Journal on Applied Mathematics, 2002; 62 1019-1043.

17. Tony, F., Chan, et al.: Nontexture Inpainting by Curvature-Driven Diffusions. Journal of Visual Communication and Image Representation, 2001.

18. J. Cao, Y. Li, Q. Zhang, et al.: Restoration of an ancient temple mural by a local search algorithm of an adaptive sample block. Heritage Science, 2019; 7 (1).

19. J. Cao, Z. Zhang, A. Zhao, et al.: Ancient mural restoration based on a modified generative adversarial network. Heritage Science, 2020; 8 (1): 7.

20. Lilong Wen, Dan Xu, Xi Zhang, et al.: The Inpainting of Irregular Damaged Areas in Ancient Murals Using Generative Model (in China). Journal of Graphics, 2019; (5): 925-931.

21. X. Ren, P. Chen: Murals inpainting based on generalized regression neural network (in China). Computer Engineering and Science, 2017; 039 (10): 1884-1889.

22. J. Liu, Intelligent Image Processing and Inpainting for Ancient Fresco Preservation (in China), Zhejiang University, Hangzhou, 2010, pp. 20-30.