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RESEARCH ARTICLE

Research on Deep Learning-Driven High-Resolution Image Restoration for Murals From the Perspective of Vision Sensing

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ABSTRACT Due to the fact that murals are usually displayed on a large area, it is necessary to develop intelligent algorithms for high-resolution images. In recent years, deep learning has been widely applied in the field of image processing. For the problem of high-resolution image restoration in murals, deep learning technology can also be used to solve it. This article carries out systematic research on deep learning-driven high-resolution image restoration for murals from the perspective of vision sensing. Firstly, principal characteristics of mural paintings such as textures and structures are extracted using conventional vision feature representation. Then, the extracted feature contents are mapped into restorage schemes with the assistance of deep neural network structure, so that digital restoration of mural paintings can be realized. The proposed solution blocks high priority sample blocks, prevents sample blocks with a large number of unknown pixels from being processed, and reduces the continuous accumulation of errors caused by matching errors to achieve digital restoration of murals. The simulation results on real-world image sets show that compared to the baseline method, the recovery accuracy can be improved by more than 20%. This method can restore the main structure and texture details of complex scene images, especially in the case of large-scale information loss.

INDEX TERMS Image restoration, digital restoration, high resolution image, deep learning.

I. INTRODUCTION

Under the background of digital new media, the dynamic visual art develops rapidly. Generally, audiences prefer moving images with sound to receive new information. No matter in the mobile TV or large public places around us, we can find that the traditional static print advertisement has quietly faded away, and it has been replaced by dynamic images with rich changes and more eye-catching [1]. Most of the large-scale advertising media begin to favor dynamic videos that can be played circularly and are full of dynamic interest, so as to meet the sensory psychological needs of modern people for on-site interactivity and interest [2]. In image restoration, the physical restoration is generally carried out by specialized painters with special tools, pigments and special materials. Painters need certain professional knowledge to be competent, and it is generally the restoration of items with important value [3]. Digital image inpainting is an important research content in the field of computer vision, and it is a technology to automatically repair the lost information in an image by using known information [4]. Through inpainting, the repaired image can achieve a visually reasonable effect, even if the observer can't see that the image has been repaired [29].

As one of the artistic treasures of Chinese traditional cultural relics, temple murals have made indelible contributions to the inheritance and development of Chinese civilization, and are China's important cultural heritage and wealth. However, many murals have different degrees of diseases, which affect the picture content. The traditional manual repair

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work is irreversible, so there are certain risks [30]. Chinese traditional murals are quite rich in content. According to rough statistics, there are a large number of temple murals in Shanxi. However, due to the backwardness of protection technology and the lack of attention of relevant departments, many murals are gradually being damaged by nature and man-made in varying degrees [4]. Due to the remote geographical location of ancient murals, harsh surrounding environment, natural damage caused by various factors such as earthquakes, insect pests, humidity, etc., now unearthed murals are faced with many problems, such as caustic soda, nail peeling, hollowing, shedding, fading and so on [5]. Light acts on the visual organs and excites the cells that feel it, and its information is processed by the visual nervous system to produce vision. Through vision, human beings can get all kinds of information such as the size, brightness, movement and color of external objects [6].

Traditional image restoration techniques typically use methods such as interpolation or noise reduction. These methods all process images, which may lead to image distortion or an increase in the degree of distortion. Therefore, it is not applicable to color restoration issues. It is especially important for the sustainable development of traditional mural art in the new era to apply digitalization to traditional art forms and combine mural art with the development of modern digital comprehensive new media art by using new media [7]. Digital image inpainting technology refers to those images that have their own defects, or some objects in the images need to be repaired and filled according to a certain mathematical model, or the objects in the images are removed to restore the image integrity and achieve the required visual effects [8]. Chinese culture has become an indispensable precious treasure in the world culture after the precipitation of countless sun and moon. In this long history, countless cultural relics and historic sites have been handed down, providing rich materials and materials for future generations to study the history and culture of the Chinese nation [9].

In the practical application of digital image processing, the presence of noise is inevitable. In theory, image restoration is the process of restoring high-quality images from noisy images using appropriate techniques. Khmag et al. proposed clustering based natural image denoising using dictionary learning algorithms in the wavelet domain [10]. Khmag et al. proposed an automatic estimation method of additive Gaussian white noise based on local statistics. The experimental results show that the proposed algorithm can effectively execute over a wide range of visual content and noise conditions, as well as under additive noise. Combined with different traditional noise estimators, the proposed algorithm produces the best performance, higher quality images, and faster running speed [11]. Digital data modeling of cultural relics refers to the scientific calculation method, which uses the collected cultural relics information to calculate, and finally obtains the real three-dimensional digital model of cultural relics [12]. The digital mural restoration work does not need to deal with the original works directly, which can provide sufficient scientific basis for the physical protection and restoration process of murals and help to reduce the danger of mural restoration work. In the research of computer-aided digital restoration of temple murals, the main contributions of this paper are as follows:

(1) In this paper, an image inpainting method based on offset matching of sample blocks is proposed. Aiming at the problem that the traditional matching method based on sample blocks is easy to cause the failure of inpainting results due to the accumulation of matching errors, it is improved by two strategies.

(2) When the priority of the sample block is determined, the model only calculates the data items of the sample block to ensure the continuity of the structural features in the repair results. At the same time, the repair process is repaired layer by layer along the damaged area by marking to ensure the credibility of the repair process.

This article proposes a high-resolution image processing technology based on deep learning. This technology occludes high priority sample blocks to prevent sample blocks with a large number of unknown pixels from being processed. And reduce the continuous accumulation of errors caused by matching errors, thereby achieving digital restoration of temple murals. The research structure is divided into the following parts. Section II describes the content of inpainting algorithm in different image directions. The application and development of digital inpainting technology in the field of cultural relics restoration are analyzed through different research results. Section III analyzes digital image restoration algorithm and mural inpainting based on depth learning. The inpainting method using sample block matching has achieved good results in repairing large area of image damage and removing large objects in the image. Section IV verifies the effectiveness of the proposed deep learning based digital restoration model for mural images. We compared traditional digital restoration methods for mural images through comparative simulation experiments. Section V summarizes the entire text, and the design method proposed in this article can effectively solve the problems of unclear images and insufficient stereoscopic perception. Simultaneously maintaining the clarity of the mural image. Compared with traditional algorithms, the recovery accuracy has been improved. The restoration effect using the proposed method is significantly better than other comparison methods, and the background information is better suppressed.

II. RELATED WORK

Image restoration comes from art restoration, which simulates the process of artificial restoration. Since the appearance of image inpainting technology, it has been widely concerned by many researchers. To solve various problems in image inpainting, they have put forward many valuable image inpainting algorithms. Costantini found through comparison that although the accuracy of data collection by image mosaic method is slightly lower than that by scanning method, the data collection by image mosaic method is more flexible, and the high-fidelity scanning range of scanning method is too small compared with mural painting [13]. Kim et al. proposed an image inpainting algorithm based on the direction interpolation of image gray gradient, and analyzed the topological structure and texture information in the image during inpainting [14]. Experiments show that the algorithm has a good effect on both image topological structure repair and texture information extension. Xu et al. proposed a digital inpainting algorithm based on image layering [15]. Firstly, the algorithm transforms the image, divides the image to be repaired into different layers, and then repairs the separated layers by using the repair algorithm. Finally, the application layer fusion method finds the most suitable repair strategy for the divided layers.

Dong applied the global variational method to vector images according to the idea of vector image coupling [16]. The experimental results show that the improved inpainting model can keep the edges of color images, and has a good denoising function. Memik et al. digitized the partial differential equation of the original model, transformed it into a weighted average form, and directly calculated the missing pixels by using adjacent known pixels. The weighting coefficient was determined by the gradient and curvature, and the repair order was determined by the gradient variance of known pixels in the neighborhood of the point to be repaired [17]. Cai et al. put forward an improved TV model image inpainting algorithm, which combines isotropic diffusion and anisotropic diffusion, and makes use of regional frequency difference to realize using different iterative equations in different regions [18]. García-Diego et al. decomposed the TV model into several sub-Eulerian-Lagrange equations by adding new control variables, and solved the iterative problem of the sub-equations for image inpainting, which greatly improved the inpainting efficiency [19]. Based on the image sparse representation model, Conkey et al. added a hidden Markov tree structure model in order to obtain more correlations between adjacent scale wavelet coefficients, which can adjust the correlation of wavelet coefficients between scales, thereby improving the Accuracy of Image Reconstruction [20].

PSNR is the most common and widely used objective measurement method for evaluating image quality, but many experimental results show that PSNR scores cannot be completely consistent with the visual quality seen by the human eye. It is possible that those with higher PSNR may appear worse than those with lower PSNR. This is because the sensitivity of human vision to errors is not absolute, and its perception results can be influenced by many factors and change. SSIM models distortion as a combination of three different factors: brightness, contrast, and structure. Use mean as the estimate of brightness, standard deviation as the estimate of contrast, and covariance as a measure of structural similarity. Due to its outstanding performance, SSIM has become a widely used method for measuring video quality in broadcasting and cable television. It has wide applications in super-resolution and image deblurring. VMAF is a set of tools built using machine learning. This tool can accurately predict image quality distortion under HTTP streaming technology, including compression distortion and scaling distortion. VMAF has been integrated into ffmpeg 1. The application of digital image restoration technology in the field of cultural relics restoration has become an inevitable development trend of computer technology and traditional cultural relics restoration methods. In the research of computer-aided digital restoration of temple murals, this paper proposes an image restoration method based on sample block offset matching, which offsets the high-priority sample blocks to avoid the processing of a large number of sample blocks with unknown pixels, thus realizing the digital restoration of temple murals.

III. METHODOLOGY

A. DIGITAL IMAGE RESTORATION ALGORITHM

Digital mural painting has developed into a trend and is used by more and more countries. Digital mural painting images can exist independently from the mural painting itself, and all the information of mural painting can be preserved intact. In the long-term preservation, many murals will naturally die out or disappear due to human destruction. Before that, it is necessary to collect the mural images, keep their information permanently, repair them later, and make them into visual products for future generations [21]. Through analysis, it can be found that there are many repetitive patterns in mural images, which can be repaired by referring to the surrounding areas or other well-preserved similar mural images of the same era. Therefore, in order to overcome the defects of image restoration algorithm based on samples, the concept of mural image database is introduced in the process of image restoration. When no similar block can be found in the sample resources of the damaged image itself, it can be searched in the image database. The image segmentation process of mural art style extraction is shown in Figure 1.

Image inpainting method using sample block matching has achieved very good results in repairing large-area image damage and removing large objects in the image. The inpainting process based on sample block matching is actually a method based on local region growth, and its basic idea is to ensure the local consistency of pixels, and at the same time, each time the known region grows, the unknown region is filled. Specifically, by directly matching the blocks that are most similar to the known information in the blocks to be filled in the spatial domain of the image, the pixel values corresponding to the most similar sample blocks are directly copied and stitched to the unknown area to realize growth filling. According to the different growth modes, there are two types: increasing only one pixel or increasing one block each time. The process of mural identification and model training is shown in Figure 2.

In the process of digital protection of frescoes, aiming at the restoration of damaged frescoes, the restoration principle adopted in this paper is structure before texture, whole before part. First of all, it is the image acquisition. Good acquisition

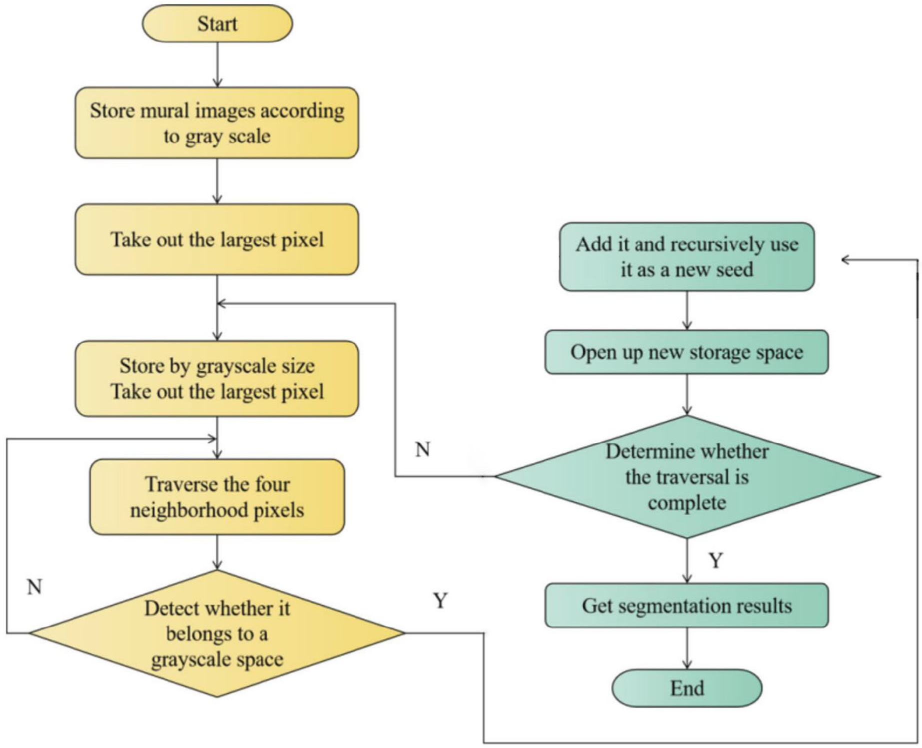

FIGURE 1. Extraction of mural art style.

can preserve the damaged area with high definition, which greatly improves the restoration results. Secondly, the digital images of murals are preprocessed to eliminate noise. Then judge whether the damaged area is structural damage or texture damage, and adopt their own methods to determine the damaged area. Finally, according to the difference of the size and category of the defect area, different repair techniques are adopted to repair it. Let the gray value range of the original mural image $f(x, y)$ be $(g_{\min}, g_{\max})$, choose a suitable threshold T, and:

$$g_{\min} \leq T \leq g_{\max} \tag{1}$$

Image segmentation with a single threshold can be expressed as:

$$g(x, y) = \begin{cases} 1, & f(x, y) \geq T \\ 0, & f(x, y) < T \end{cases} \tag{2}$$

where $g(x, y)$ is a binarized image. The object can be easily revealed from the background through binarization. The key to binarizing the mural image is the reasonable selection of the threshold.

The value of the research on mural evolution simulation technology lies not only in providing a visual medium for the mutual communication between conservationists, but also in predicting its changing trend under the influence of external factors by applying the evolution law to murals, even if corresponding measures are taken to protect them in time.

Let the gray function of the two-dimensional mural image be $f(x, y)$. The r $(r > 0)$ field of the (i, j) loxel is defined as the following set:

$$N_r(i, j) = \{(k, l) \,|\max\{|i-k|, |j-l|\} \leq r\} \tag{3}$$

The value defined as follows is called the interest degree of the (i, j) bit pixel:

$$I(i, j) = \frac{1}{(2r+1)^2 - 1} \sum_{(k,l)\in N_r(i,j)} (f(i, j) + w(k, l, \sigma) \times f(k, l)) \tag{4}$$

Among them:

$$w(k, l, \sigma) = \psi(i-k, j-l, \sigma) \tag{5}$$

where $\psi(x, y, \sigma)$ is the DOG function. Scale, rotation, illumination change, structure, texture and semantics will affect the quality of image inpainting, which brings some difficulties to inpainting. For scratches, words and other small areas, generally good repair results can be obtained. However, in image inpainting, it is often necessary to repair a large area, such as the removal of objects and the completion of scenes [22]. At present, it is still a difficult problem to repair a large area. Through the study of the sample blocks in the search domain of mural images, it is found that many adjacent sample blocks are similar in color and structure, and the information of the overall image structure is not complicated. At the same time, there are continuous large blocks of similar

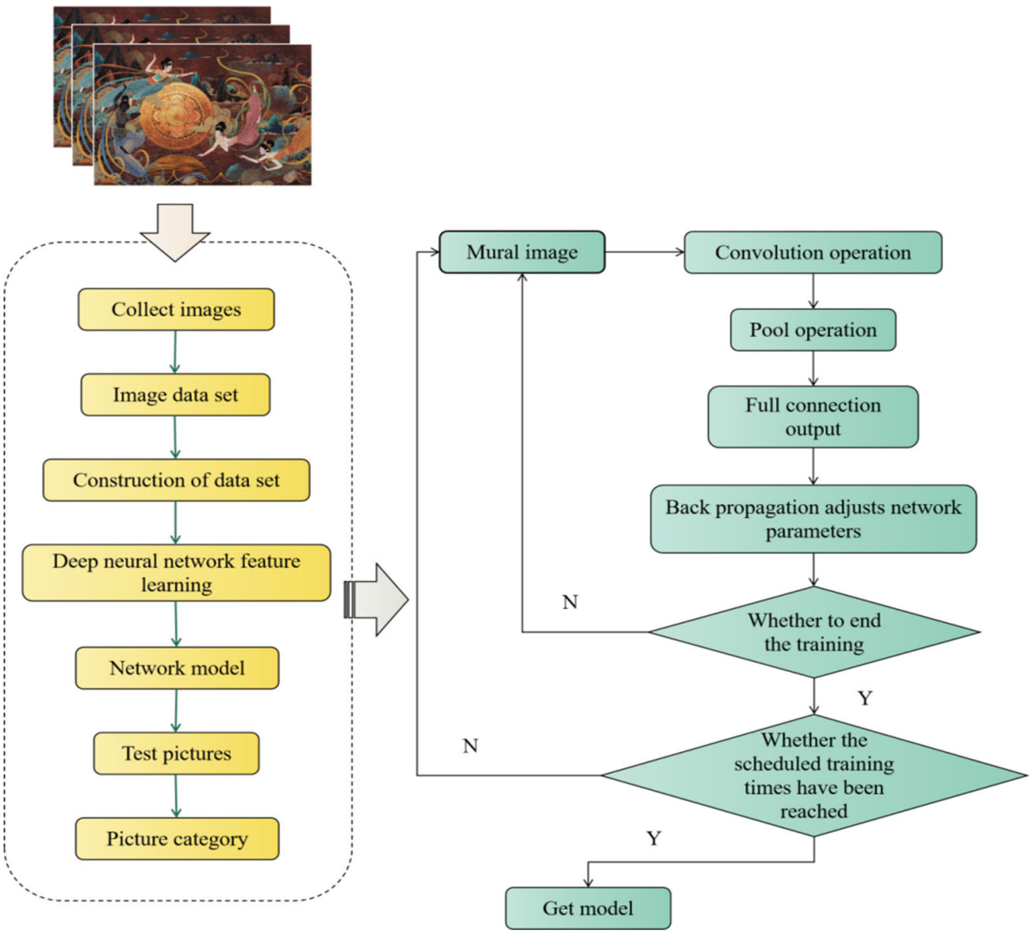

FIGURE 2. Mural recognition and model training process.

colors in the images, and there is a large redundancy between adjacent sample blocks. When repairing the damaged parts of mural images, global search will waste a lot of time. Therefore, we consider reconstructing the image sample area to reduce the redundancy of sample blocks and improve the efficiency of the algorithm.

B. DEEP LEARNING-BASED MURAL IMAGE INPAINTING

The static images represented by photos, art works, etc. and the dynamic images represented by mobile phones, televisions, computers, videos, animations and flash often appear in our lives, forcing people to passively accept and adapt to this cultural change. Vision is a collective name of culture which is based on image symbols and takes visual perception as its external manifestation [23]. Visual culture changes with visual factors, visual social life changes with visual objects, and visual objects become images, which is an impact on pure language. In the article of digital image virtual restoration, the crack detection is the removal and restoration of it. When repairing the missing pixels, the pixel-based inpainting method extends from the boundary of the damaged area to the center, which can keep the extension of the image structure, thus ensuring the spread of the line structure and the image outline. Figure 3 shows the convolution operation process of the mural fast recognition model.

As an art work in a new era, it must have its own uniqueness first, so that it can be attracted by people and emerge in the current works with various forms. The design of dynamic mural belongs to the category of visual design, and the design should focus on the uniqueness of artistic style and the intensity of visual impact [24]. In artistic creation, we should first associate the picture effect, and then use logical thinking to determine the elements that need to move in the picture. How can the audience quickly integrate into the work, and create a good visual environment and interactive effect while highlighting the content of the work? DepthWise (DW) convolution is a convolutional form with the same number of input and output channels and packets. Unlike traditional convolutions, each convolution kernel in DW convolution only calculates the corresponding feature map, and the parameter and computational complexity are 1/n of the original (n is the number of input channels). Although DW convolution can reduce a large number of parameters, it will reduce the information exchange between feature pixels in different layers, ultimately resulting in a loss of accuracy.

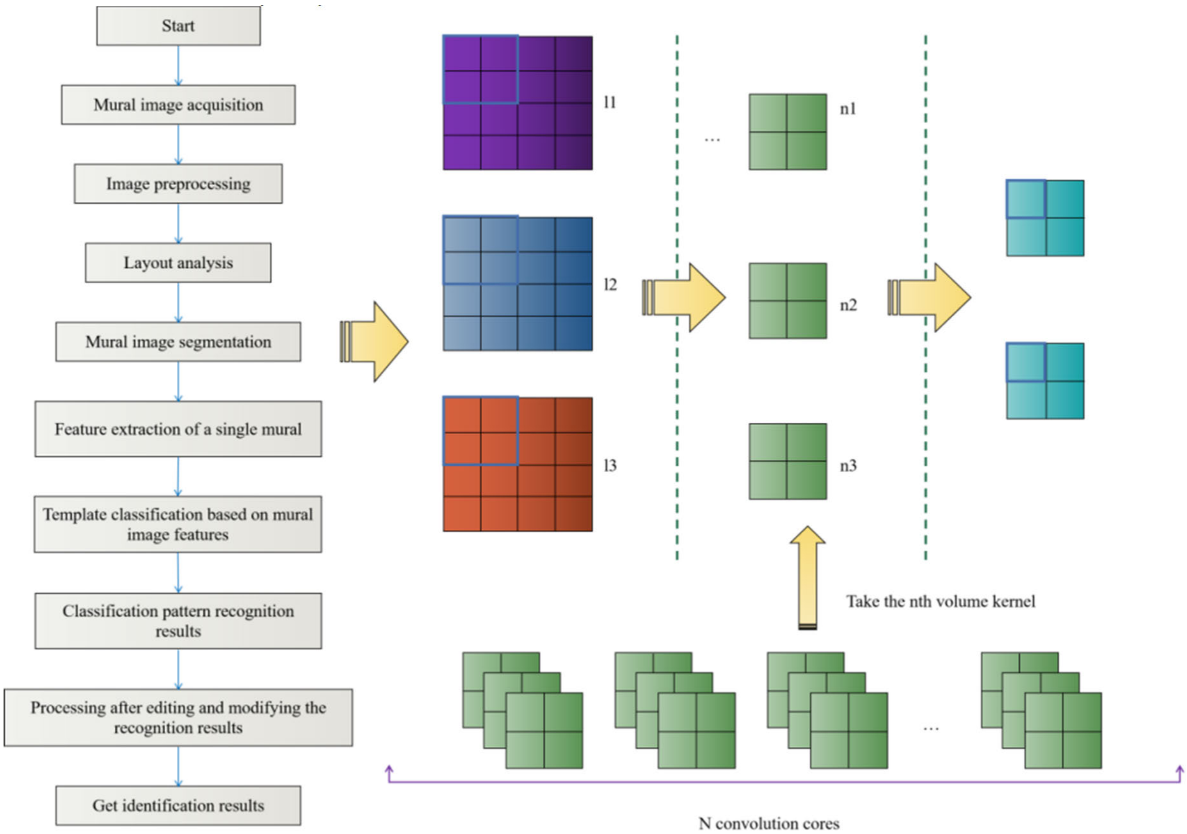

FIGURE 3. Rapid recognition model of murals.

Large convolutional kernels rely on residual connections. This article uses MobileNetV2 as the baseline network for experiments. Take 3 of the deeply separable convolutions in the baseline network × Replace the 3-size convolutional kernel with 13 × After retraining, the classification accuracy of a 13 size convolutional kernel increased by 0.77%. However, after removing the residual structure in the model, the accuracy is only 53.98%. It can be concluded that the residual structure has a much greater benefit for large convolution kernels than for small convolution kernels. Therefore, in models with large convolution kernels, the residual structure is crucial. Only in this way can we attract the audience and further understand the spiritual connotation conveyed by the work. Convolution is an operation applied to 3D tensors, called feature maps. These feature maps consist of two spatial axes (height and width) and one depth axis (or channel axis). If we consider the example of RGB images, height and width constitute the spatial axis, and three color channels represent the depth axis. Similarly, for black and white images, the depth is 1. But in the output of other layers, depth is not represented by color channels, but rather represents filters. Convolutional operation consists of two key parameters, Kernel size: The size of the filter applied to the image. These are typical 3 × 3 or 5 × 5. Depth of output feature map: This is the number of output filters calculated by convolution. The convolution neural network function is defined as:

$$x_j^l = f\left(\sum_{i\in M_j} x_i^{l-1} \times k_{ij}^l + b_j^l\right) \tag{6}$$

In the formula, x_i represents the input feature map, k represents the convolution kernel, b represents the bias term, and the output after convolution is the feature map x_j. Suppose the convolutional layer uses k filters to convolve the input mural image, generating k new feature maps for subsequent processing. represents the output feature map in a layer, then:

$$F_j^{(n)} = \sum_i w_{ij}^{(n)} * F_i^{(n-1)} + b_j^{(n)} \tag{7}$$

where $*$ is the two-dimensional convolution; $w_{ij}^{(n)}$ and $b_j^{(n)}$ are the convolution filter and bias, respectively; $F_j^{(n)}$ is the j^{th} output feature map in the n^{th} layer. The activation layer formula after the convolutional layer is as follows:

$$F_j^{(n+1)} = f\left(F_j^n\right) \tag{8}$$

where f is the pointwise activation function. Convert each data item x_i to y_i in a mini-batch $B = \{x_1, x_2, x_3, \ldots, x_m\}$

of size m:

$$y_i = \gamma \widehat{x}_i + \beta \tag{9}$$

$$\widehat{x}_i = \frac{x_i - E_M(x_i)}{\sqrt{Var_M(x_i) + \varepsilon}} \tag{10}$$

where $E_M(x_i)$ and $Var_M(x_i)$ are the mean and variance in batch B, respectively.

In fact, under certain assumptions, we can use maximum likelihood to obtain the form of mean square error loss. Assuming that the error between the model prediction and the actual value follows a standard Gaussian distribution. This is actually the form of mean square error loss. That is to say, under the assumption that the error between the model output and the real value follows the Gaussian distribution, the minimum mean square error loss function is essentially consistent with the maximum likelihood estimation. Therefore, in scenarios where this assumption can be satisfied (such as regression), the mean square deviation loss is a good choice for loss function. When this assumption cannot be satisfied in scenarios such as classification, the loss of mean square error is not a good choice. The effect of image restoration often depends on people's subjective visual feeling. The image information is specifically obtained through human eyes. Through long-term experience accumulation, human beings have formed a set of inherent cognitive principles for the received images [25].

In order to deal with the complex line and color information of murals, we use a mixed way of frame and rules to organize and express knowledge [26]. Establish a sample knowledge base including vector diagrams of line drawing elements and color information. Through the study of the artist's drawing sample library, the final line drawing replacement result is generated. In the long history, mural art has always been associated with people's life style. It is the artist's way of painting on the wall to convey certain ideas to the viewers, which reflects various changes in people's life and society in different times. As mural art predates the appearance of words, as one of the early civilizations in human history, mural art not only plays a role in decorating and beautifying the environment, but also has certain practical functions. The neural network structure of mural stereoscopic enhancement is shown in Figure 4.

In deep learning, supervised learning defines a model and estimates the optimal parameters based on data from the training set. The gradient descent method is a parameter optimization algorithm widely used to minimize model errors. The gradient descent method involves multiple iterations and minimizes the cost function in each step. The learning rate will control the learning progress of the model during the iteration process. In the gradient descent method, a unified learning rate is given, and the entire optimization process is updated with a determined step size. In the early stages of iterative optimization, if the learning rate is high, the stride forward will be longer. At this point, the gradient descent can be carried out at a faster speed, and in the later stage of iterative optimization, the learning rate value is gradually reduced and the step size is reduced. This will help with the convergence of the algorithm and make it easier to approach the optimal solution. The features of the given two images are represented by x and y. Assuming that the mural image is represented as an d-dimensional feature vector, the features of the given two images are:

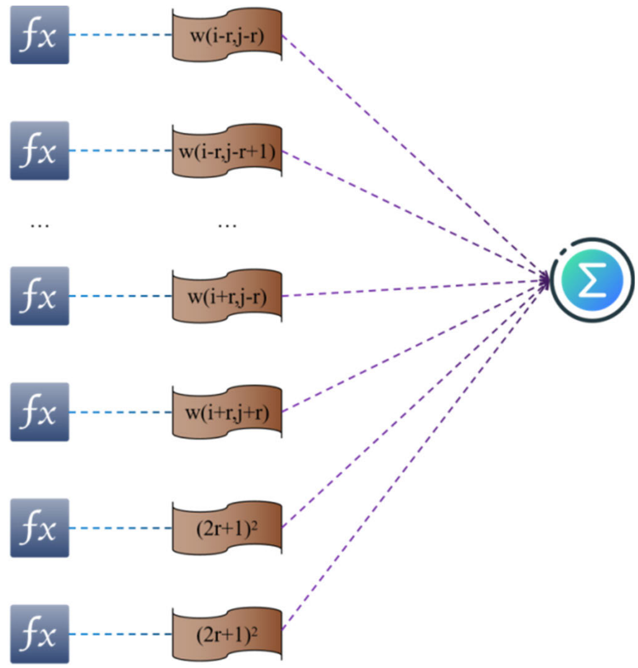

FIGURE 4. Stereo-enhanced neural network structure for mural images.

$$x = (x_1, x_2, \ldots, x_d)^T \tag{11}$$

$$y = (y_1, y_2, \ldots, y_d)^T \tag{12}$$

where $x_1, x_2, \ldots, x_d$ is the eigenvalues of the x of the T-order equation. Similarly, $y_1, y_2, \ldots, y_d$ is the eigenvalues of the y of the T-order equation. The cosine of the angle between them can be used as a similarity measure:

$$Sin_t(x, y) = \frac{x \cdot y}{\|x\| \, \|y\|} \tag{13}$$

where x and y are representation of a pair of objects. The distance between two histograms can be measured by histogram subtraction:

$$D_h(x, y) = \frac{\sum_i^d \min(x_i, y_i)}{\min\left(\sum_i^d x_i, \sum_i^d y_i\right)} \tag{14}$$

Minkowski distance is defined as:

$$D_p(x, y) = \left(\sum_{i=1}^d |x_i - y_i|^p\right)^{1/p} \tag{15}$$

In order to distinguish the role of different feature components in the similarity measure, their weighted form is

TABLE 1. Comparison of detection effects without noise.

	Original image	Robert	Sobel	Prewitt	LOG
Edge points	680	582	556	538	564
Detection ratio	-	82.8%	81.9%	78.4%	82.9%
Misjudgment point	-	None	Basic none	None	None

TABLE 2. Comparison of detection effects when Gaussian noise is added.

	Original image	Robert	Sobel	Prewitt	LOG
Edge points	680	521	545	519	536
Detection ratio	-	77.5%	80.9%	78.8%	80.2%
Misjudgment point	-	Basic none	Have	Have	Basic none

TABLE 3. Subjective assessments given by observers to mural images.

Sample set	WT	Article method
1	4.5	3.6
2	4.2	3.1
3	4.6	3.9
4	4.8	3.5
5	4.7	3.8

often used:

$$D_1(x, y, w) = \sum_{i=1}^{d} w_i |x_i y_i| \tag{16}$$

Quadratic distances are also frequently used, the main of which is the Mahalanobis distance, defined as:

$$D_2(x, y, M) = \sum_{i}^{d} \sum_{j}^{d} m_{ij} (x_i - y_i) \left(x_j - y_j\right) \tag{17}$$

where M is a real symmetric matrix. If M is restricted to a diagonal matrix, the weighted Euclidean distance can be obtained.

Training deep learning models requires millions of iterations, making the process of finding bugs very difficult and prone to crashes. Therefore, we should start from a simple place, step by step. For example, model optimization (such as regularization) can always be carried out after code debugging. In addition, we also need to frequently visualize the prediction results and model metrics, and we first need to make the model run so that there is a baseline that can be backed up. It's best not to get stuck in a large model and try to get all the modules done. In most literatures, black cracks are mainly extracted, because black cracks have obvious geometric features and low-brightness color features [27].

Different crack detection techniques generally include simple threshold segmentation, linear detection and various morphological filtering. Line drawing edge extraction and drawing are attracting more and more attention in computer art creation. The contour obtained by traditional image segmentation and edge extraction algorithms can hardly meet the artist's pursuit of artistic image [28]. In order to get a line drawing image closer to the painter's requirements, we must improve the existing edge extraction algorithm, and find an intelligent and interactive method suitable for computer processing from different aspects such as intelligence, mathematics and painting. In most cases, the traditional single method of color image segmentation can't achieve satisfactory results, but the segmentation effect can be greatly improved by mixing segmentation methods according to different application fields.

IV. RESULTS ANALYSIS AND DISCUSSION

The experimental data includes 1300 images from a number of real-world mural paintings. They were collected from 2020-2021 by our research team. The 1300 images are with 50 different shapes. In each shape, 5 images are used for testing and others are used for training. The network model construction in this article is based on the TensorFlow 1.0 framework, and the Rtx2080 i training dataset is used in the experiment. During the training process, control the initial learning rate to 0.001. During the training process, the learning rate exponentially decays in an adaptive manner. After many times of learning, the loss function decreases and tends to be stable. At this point, the training is over.

Image inpainting is a process of reasoning. The data of unknown part is inferred according to the prior information of known part of the image, and the reasoning is based on the prior knowledge of the image. Therefore, the prior model based on visual psychology is very important for image inpainting technology. According to Gestalt theory, the main structure of natural images should be complete, and the images should have continuity and smoothness, which are the prior information set by common image inpainting methods. In order to verify the effectiveness of the proposed digital restoration model of mural images based on deep learning,

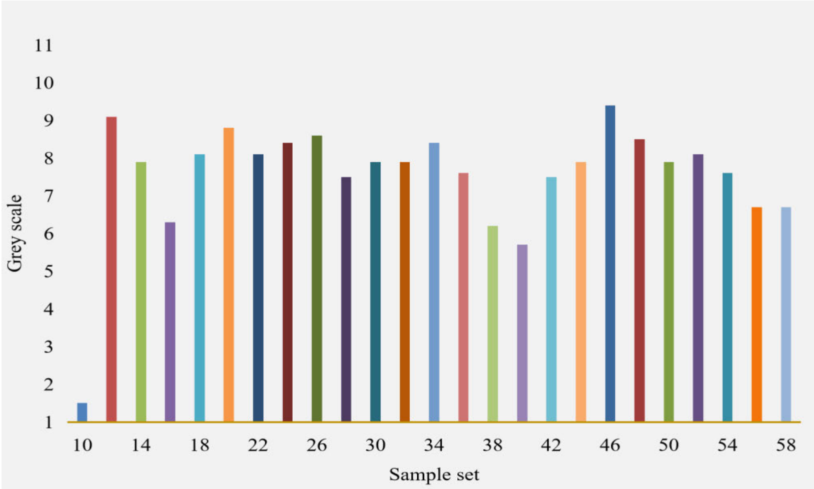

FIGURE 5. Grayscale histogram of the original mural image.

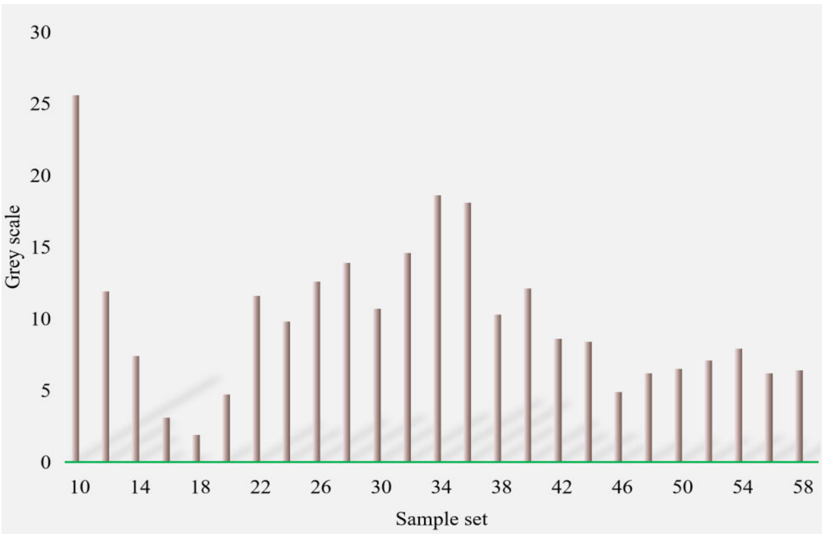

FIGURE 6. Grayscale histogram after digital restoration model enhancement.

the traditional digital restoration methods of mural images were compared by comparative simulation experiments. The detection effect of the operator is evaluated by the number and accuracy of edge pixels, as shown in Table 1. The misjudged points in the table indicate that the non-edge points are judged as edge points. In practice, most of the mural images processed are those polluted by noise, even if smooth denoising is done before processing. Table 2 shows the comparison results of detection effect when Gaussian noise is added. Gaussian noise is one of the typical noises, so LOG operator has high practical value. Figure 5 shows the gray histogram of the original mural image. Figure 6 is the gray histogram enhanced by the digital restoration model of mural image in this paper.

The contrast method can repair the characteristic information of mural images to a certain extent, but while enhancing the characteristic information of mural images, it also enhances the redundant background information of mural images, which is prone to over-enhancement. Although the main purpose of image inpainting is to satisfy people's cognition of visual psychology, since this field has been widely studied, a large number of methods have appeared, and different methods have different inpainting effects. Subjective evaluation refers to judging the effect of image restoration from the perspective of visual psychology. Because of the difference of individual experience and educational background, everyone must have a strong subjective consciousness and emotion when evaluating the image inpainting effect. Therefore, the subjective evaluation of restoration effect needs some guidance. Table 3 and Figure 7 show the subjective evaluation test results of mural images given by observers. Figure 7 uses 10 random survey samples from the dataset and

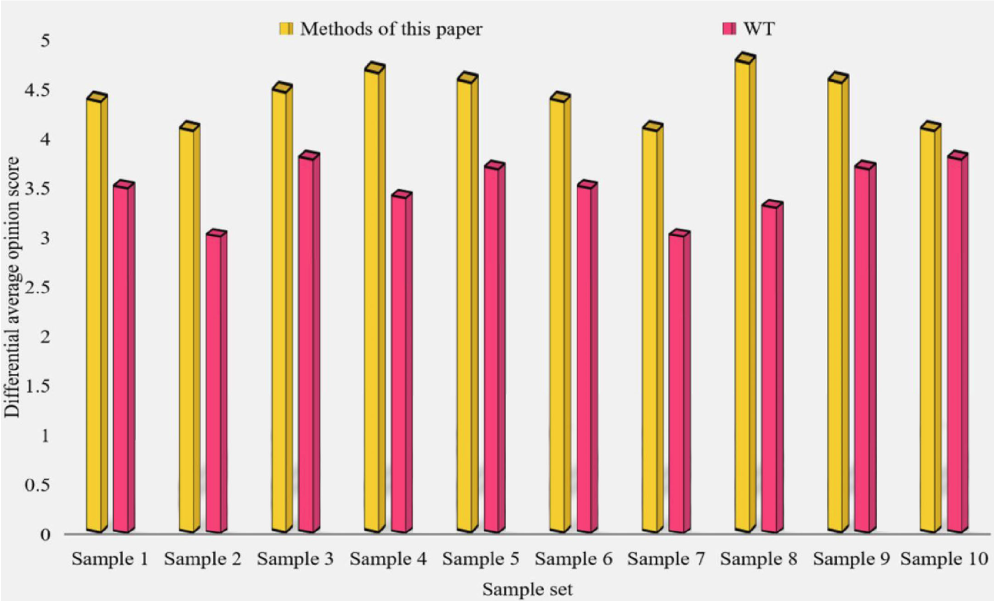

FIGURE 7. Subjective assessments given by observers to mural images.

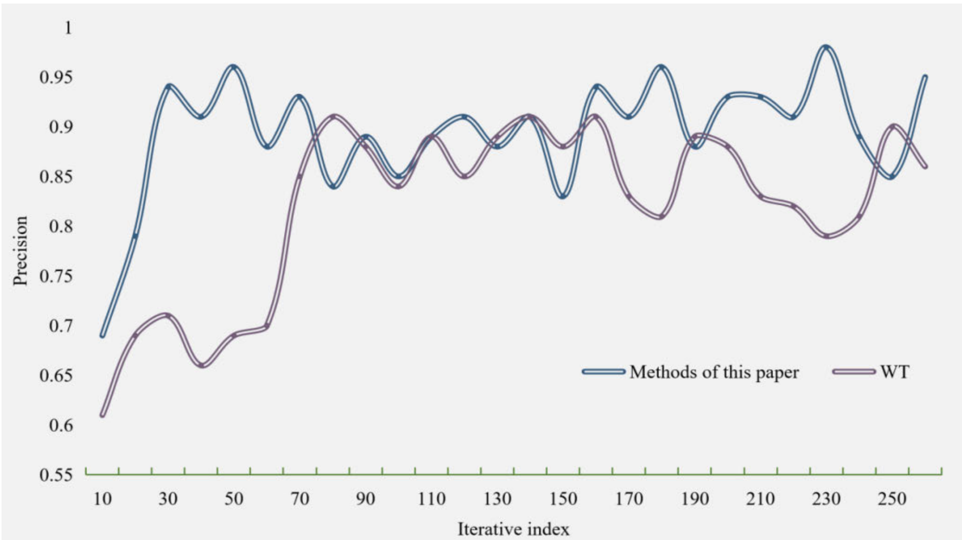

FIGURE 8. Accuracy results of different algorithms.

compares the experimental results of our method and wavelet transform (WT).

The experimental results show that the digital restoration model of mural images in this paper can effectively maintain the local structure of mural images and enhance the contrast and stereo of images. The art of dynamic graphics and images has frequently appeared in people's field of vision, and dynamic mural painting is to apply traditional art forms to modern digital dynamic media, so that ''modernity'' and ''tradition'' can be mutually integrated and used for reference. As a traditional art, mural painting is a precious wealth left by history. The protection and inheritance of mural painting should also meet the aesthetic requirements and viewing methods of modern people, so that traditional art can rekindle the public's interest in tradition and classics. As a new form of artistic expression, digital mural is rich in interest, strong sense of scene, real interaction and powerful information carrying capacity, so it is more in line with contemporary characteristics and new appreciation ways. Figure 8 shows the precision results of different algorithms.

The design method of digital restoration model of mural image based on deep learning proposed in this paper can effectively solve the problem of unclear image and insufficient stereo, while maintaining the clarity of mural image. Compared with the comparison algorithm, the highest accuracy is improved by 29.66%. Using the proposed method to restore the characteristic information of mural images, the restoration effect is obviously better than the other two

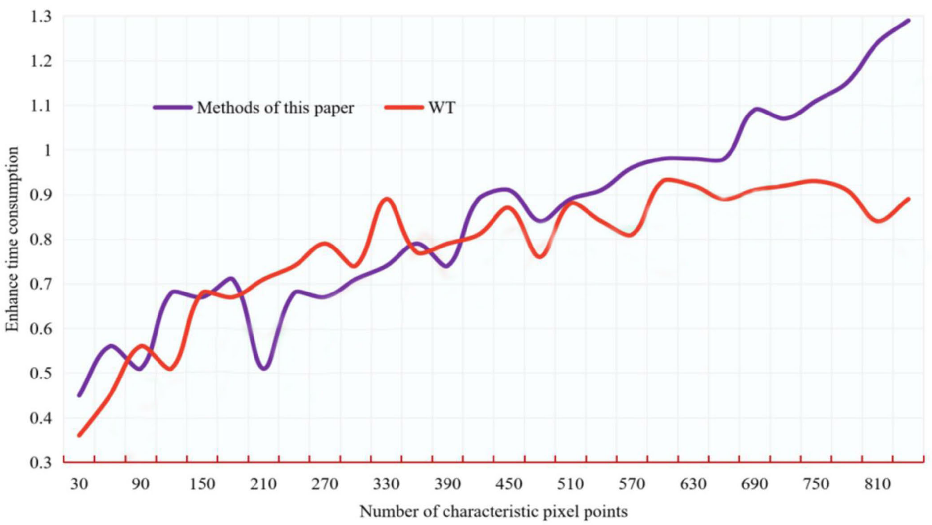

FIGURE 9. Time-consuming comparison results of enhanced image processing effects of different methods.

contrast methods, and the background information is better suppressed. Although the edge sharpening method enhances the image contour, the details will be blurred, and the overall effect is not ideal. Although the mural image enhanced by the traditional wavelet transform method highlights the edge of the image after edge sharpening, compared with the digital restoration method proposed in this paper, there is still some ambiguity in detail processing. Comparing and enhancing the image processing effect by different methods takes time for comparative analysis, as shown in Figure 9.

As can be seen from the figure, the image processing effect of digital restoration of mural images by traditional methods takes the longest time as the number of pixels of feature information increases. Although the image processing time of digital restoration of mural images based on wavelet transform is shorter than that of traditional methods, it still shows an increasing trend. One of the main criteria of image restoration judgment is the structural similarity between the restored image and the original image. Essentially, natural images have extremely high structure, and when the image spaces are similar, it is mainly manifested in the strong correlation between the pixels of the images. These correlations carry important information about the structure of objects in the visual scene. Therefore, the approximate information of image difference can be perceived by detecting the change of image structure information.

V. CONCLUSION

Because of the remote geographical location and harsh surrounding environment of ancient murals, they suffered from the natural damage caused by various factors such as earthquakes, insect pests, humidity, etc., as well as the damage caused by people's development of murals and some intentional or unintentional damage. Digital image restoration is an important research content in the field of computer vision, and it is a technology to automatically repair the lost information in images by using known information. In this paper, a high-resolution image processing technology based on deep learning is proposed, which blocks the high-priority sample blocks, prevents the sample blocks with a large number of unknown pixels from being processed, and reduces the continuous accumulation of errors caused by matching errors, thus realizing the digital restoration of temple murals. The design method of digital restoration model of mural image based on deep learning proposed in this paper can effectively solve the problem of unclear image and insufficient stereo, while maintaining the clarity of mural image. Compared with the traditional wavelet transform, the restoration accuracy of mural image of this algorithm is improved by 29.66%. Using the proposed method to restore the characteristic information of mural images, the restoration effect is obviously better than the other two contrast methods, and the background information is better suppressed.

In the future research process, it is necessary to fully understand the traditional art, absorb the essence, combine advanced digital technology to improve the artistic taste of the creative objects, properly show the cultural connotation of the works, and make the traditional mural art more diversified, so as to practice and explore new artistic expressions.

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