Overview of Digital Image Inpainting Technology

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ABSTRACT

As an important part of image processing, digital image inpainting is more and more widely used in daily life. Its main repair method is to automatically recover lost information based on the existing information of the damaged image. The article first explains the concept and application of image inpainting; secondly, it outlines the current main image inpainting techniques and main evaluation methods; and finally, the prospect of image inpainting techniques.

KEYWORDS

Digital Image Inpainting, Texture Information, Image Quality Evaluation.

CONCEPT

Digital image repair is a technique to repair damaged images through computer programming. Its essence is to repair the damaged area based on the texture information of the undamaged area. The result of the repair requires conformity with the observation of the human eye, making it difficult to detect the traces of repair. Digital image repair technology is mainly used to repair damaged calligraphy, paintings, murals, etc., and remove or replace selected objects. In image repair technology, the information of the damaged area is often completely unknowable. The repair model that the researcher needs to establish is based on the observation of human vision and based on the information of the unimpaired area to predict and fill the area to be repaired. The solution of image

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repair technology is often not unique, but it is an uncertain problem in itself, and it is difficult to obtain the authenticity of the original image in the end. Nevertheless, researchers continue to try various methods to improve the effect of image inpainting.

APPLICATION

With the development of the times, people are increasingly demanding visual quality, so the role of digital image inpainting technology in digital image processing is becoming more and more important.

First of all, in today's advanced technology, the transmission of images, videos, etc. is more and more frequent, and damage to the images during the transmission process is inevitable. This damaged image is difficult to meet the visual requirements of the human eye, so the image repair technology complements the damaged part of the image while referring to the remaining real information of the image. The image information of the damaged area is basically unknown, so the image should be repaired according to the a priori knowledge of the human eye.

Secondly, a large number of precious ancient murals, paintings and calligraphy will always be damaged to varying degrees for various reasons in history, and the inpainting of these precious paintings and calligraphy is extremely demanding to the restorer. Not only are the requirements on the inpainting materials extremely strict, but also the restorer's understanding of art must be at a higher level. Even if the above requirements have been met, one problem still to be faced is the possible error problem, which will cause further damage to the cultural relics. Therefore, the use of digital image repair can not only reduce a lot of manpower and material resources, but also avoid secondary damage to cultural relics.

At the same time, digital image inpainting also widely used in many other fields. There are:

(1) Error concealment in image and video transmission.

Video is prone to packet loss during transmission. Using digital image inpainting technology to process the blocks with errors, the video quality can be improved without changing the transmission bandwidth and communication protocol.

(2) Image encoding and compression.

At present, the structure of most image compression algorithms is transformation plus entropy coding. The transform mainly includes discrete
cosine transform, fractal transform, wavelet transform and so on. Using the repair technique to compress the image can only encode part of the image information during compression, and the rest is reconstructed using a repair method. This method uses human visual redundancy to improve coding efficiency and image quality.

(3) Repair of astronomical images.

When astronomers observe the universe, the cherished images taken by the astronomical telescope often damage the astronomical images due to reasons such as excessive distance and immature transmission technology. Digital image repair can make damaged images meet the observation requirements of human eyes to a certain extent.

METHOD

Digital image repair methods are mainly divided into image repair methods based on sparse representation, image repair methods based on texture synthesis, and deep learning image repair methods that have appeared in recent years. As shown in Figure 1:

![Digital image Inpainting method](image_url)

**Sparse Representation Method**

The image repair method based on sparse representation allows image blocks to be regarded as sparse on a certain set of bases. Since the entire image has the same sparse representation, it can repair areas of missing information in the image. Its main idea is to train the sparse representation base or low-rank rank constraint through the sparse representation or low-order rank, so as to realize the image Inpainting. The application of sparse representation in image
denoising has been successful, and it was soon applied to the field of image repair.

Its main purpose is to represent the original signal with a linear combination of as few atoms as possible in a given over-complete dictionary, thereby simplifying the expression of the signal\footnote{\cite{2}}. For image Inpainting problems, the natural image can be represented as a superposition of a small number of atoms, which can be image blocks or lines, that is, the original image can be restored and reconstructed by a small number of atoms.

The mathematical description of the sparse representation is as follows. Assuming the signal $S \in \mathbb{R}^{(n \times 1)}$, the signal $S$ can be obtained by the linear combination of $D \in \mathbb{R}^{(n \times k)}$ and $\alpha \in \mathbb{R}^{(k \times 1)}$. Where $n < k$, that is

$$S = D\alpha \quad (1)$$

In the formula, the variable $D$ is called an over-complete dictionary, each column in the dictionary is called an atom, and the variable $\alpha$ represents a sparse coefficient.

Since the dictionary $D$ is over-complete and full rank, the essence of sparse representation is to find the optimal sparse coefficient $\alpha$ in the given dictionary $D$ that satisfies the sparsity and guarantees the reconstruction of the $S$ signal. The optimization problem is mathematically defined as follows:

$$\arg\min_{\alpha} \|\alpha\|_0 \quad s. t \quad S = D\alpha \quad (2)$$

Where $\|\alpha\|_0$ is the $l_0$ norm of $\alpha$, that is, the number of non-zero elements in the vector, used to measure the sparsity of the coefficient $\alpha$. Generally, natural images will be interfered by noise or have a certain reconstruction error $\varepsilon$. When the sparsity and reconstruction error are balanced by the parameter $\gamma$, equation (2) can be rewritten as:

$$\arg\min_{\alpha} \frac{1}{2} \|S - D\alpha\|_2 + \gamma \|\alpha\| \quad s. t \quad \|S - D\alpha\|_2 \leq \varepsilon \quad (3)$$
In the sparse representation of image Inpainting, the image degradation process is formally defined as:

\[ Y = JX + n \]  \hspace{1cm} (4)

In the above formula, \( Y \) is the observed degraded image, \( X \) is the original non-missing image of \( Y \), \( J \) is the degradation matrix, and \( n \) is the Gaussian white noise. Therefore, the image Inpainting process is the process of estimating the original image \( X \) based on the degraded image \( Y \).

According to the sparse expression (3), given the dictionary \( D \), the image repair process can be transformed into a problem of solving the sparse coefficient \( \alpha \), the mathematical definition is as follows:

\[
\alpha = \arg\min_{\alpha} \frac{1}{2} ||Y - J \cdot D\alpha||_2 + \gamma ||\alpha||_1 \]  \hspace{1cm} (5)

After the sparse coefficient \( \alpha \) is obtained by equation (5), the restored image can be reconstructed by \( X = D\alpha \).

**Texture-based Synthesis Method**

The image repair method based on texture synthesis is suitable for damaged images with rich texture information. The damaged images are mainly repaired by texture synthesis technology to simulate the original texture structure of the damaged area. In 2003, Drori[4] and others pioneered the Inpainting of texture-based images. This algorithm needs to search for texture blocks in the entire image when repairing damaged images, so it takes a lot of time. Afterwards, Criminisi[5] et al. proposed a new texture image repair algorithm, matching the searched sample blocks to the damaged area in a certain order. The core idea is to consider the filling priority order of the target area, that is, when filling the target area, the priority of all target blocks on the contour is calculated, and the target blocks with high priority are filled first and updated. The Criminisi algorithm has created a new research idea, which has a significant effect both in repair time and repair effect. However, because the Criminisi algorithm needs to calculate the similarity between the sample block and the block to be matched, the repair speed is slow, and there is a problem that the priority function has low credibility.[6]
The core idea of the Criminisi algorithm is to consider the filling priority order of the target area, that is, when filling the target area, the target block with high priority is filled first and updated. The Criminisi algorithm first finds the edge $\partial \Omega$ between the entire known area $I - \Omega$ and the unknown area $\Omega$ of image $I$, and select the sample block set $P = \{p(x_1), p(x_2), ..., p(x_N)\}$ in the edge domain, where $p(x_i)$ is included in $I / \Omega$, $N$ is the total number of sample blocks, and $x_i$ is the sample. The center pixel of the block. First, the priority of pixels to be repaired is determined according to a specific principle, and the target block (the sample block) is established with the point with the highest priority as the center. Then find the template most similar to the target block in $P$, and fill the pixel value of the best matching template block into the corresponding position of the target block. In this way, after many iterations, the repair of the entire damaged area is finally completed.

Image repair based on texture synthesis is mainly divided into the following steps:

1. According to the structural characteristics of the image to be repaired, determine a sample block of appropriate size.

2. Determine the priority coefficient of each block to be repaired.

3. Copy the information in the optimal matching block to the block to be matched.

4. Repeat the above steps.

5. Until the repair of all damaged areas is completed.

The principle of image repair based on sample blocks is shown in Figure 2.
Deep Learning Method

In the study of deep learning, especially one of the feed-forward neural networks: the convolutional neural network (CNN), because each of its artificial neurons only responds to a part of the surrounding cells in the coverage area, the CNN network is in Excellent performance in large-scale image processing. In recent years, CNN-based deep learning networks have proved to be capable of capturing abstract information at high levels. At the same time, in the study of texture synthesis and image style conversion, it has been proved that the image features extracted by a trained CNN network can be used as Part of the objective function makes the image generated by a generating network more semantically similar to the target image. Coupled with extensive research on Generative Adversarial Networks (GAN), it is proved that the visual effects of images generated by the generated network can be enhanced through adversarial training. Based on these research background knowledge, image repair methods based on deep learning have been widely studied in the near future.

Based on this network structure of RNN, the Google team proposed a PixelRNN model for image repair at the 2016 International Machine Learning Conference, and achieved very good repair results. A similar structure was applied to the super-resolution reconstruction of the image and achieved very good results. The essence of the image repair method based on RNN is to use the product of the conditional probability distribution of image pixels to represent the probability distribution of the image. The repair process is to fill the missing pixels by maximizing the probability. As a generation network with self-supervised learning ability, GAN can be used for adversarial training of a certain type of image so that the generation model G has the ability to generate that type of image. The most successful application is to generate realistic face images.

In addition to the above main image repair methods, many scholars have adopted other methods to repair damaged images, and achieved good repair results. For example, Jiao Libin proposed residual learning and GAN multi-scale semantic image repair.

IMAGE QUALITY EVALUATION METHOD

Image Quality Assessment (IQA) can be used to detect the quality of the repaired image obtained by an algorithm and determine whether the repair effect of the algorithm is good or bad. So far, there is no completely unified evaluation standard for the quality evaluation of image inpainting in the world. The restored image only needs to meet visual integrity and connectivity.
The subjective evaluation method is mainly scored by the observer according to the evaluated image, and is carried out without the comparison of the original image. Generally, a test image is displayed to multiple observers, let him score or evaluate this image, and then average the observer's score. The result of the subjective evaluation is derived from the average value of a fixed number of observers. Although the subjective evaluation method can simply and directly evaluate the overall image Inpainting effect, it is affected by different subjective personal factors, and it takes a lot of time and energy.

Objective evaluation methods are easier to implement and more stable. At present, the more commonly used objective evaluation methods are mean square error, signal-to-noise ratio and structural similarity measurement. If \( f(i,j) \) is an \( M \times N \) grayscale image, its image repair quality evaluation is defined as follows:

mean square error:

\[
MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [f(i,j) - \hat{f}(i,j)]^2 \tag{6}
\]

Where \( f(i,j) \) and \( \hat{f}(i,j) \) are the original image and the restored image, respectively.

Signal-to-noise ratio:

\[
SNR = \frac{10 \log_{10} \left( \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j)^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} [f(i,j) - \hat{f}(i,j)]^2} \right)} \tag{7}
\]

In addition to the evaluation of image repair quality, comparing the results obtained with other repair methods on the repair of the same damaged image is also an important method to evaluate the effectiveness of this method.

**SUMMARY AND PROSPECT**

After the continuous efforts of a large number of scholars, various digital image repair algorithms have been continuously proposed, and the repair effect has also been significantly improved. Images with different degrees of damage have different methods of application. For example, the structure-based image repair algorithm is suitable for repairing images with a small damaged area,
while the image repair algorithm based on texture synthesis is suitable for images with a large damaged area. There are even image Inpainting methods for images such as Tangka and Dunhuang frescoes. However, we still have a long way to go in the technology of digital image Inpainting. Since the repair of digital images is based on the damaged edges of the image, the structural information of the damaged part is not known, and it is always difficult to achieve the effect of repairing to the original image. At the same time, the damaged area of digital image repair has always been manually selected, and different methods are often used for different damaged images, which greatly affects the efficiency of image repair, and a large amount of damage is still required when performing batch damaged image repair Manpower to complete. All we can do is to constantly try new methods, and continuously improve with the methods of our predecessors, and discover new problems to promote the development of digital image repair technology.

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