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Applications of Diffusion Model Image Restoration in the Field of Heritage Restoration: Overview and Outlook

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Abstract. The restoration of museum heritage is an important task with significant cultural and historical value; however, traditional methods of restoration are frequently constrained by the extent of the damage to the heritage as well as the constraints of the restoration techniques. In recent years, a method of restoration known as the diffusion model, which is based on computer vision and machine learning, has been gradually applied to the field of museum relics restoration and has shown enormous potential in relic restoration. This method of restoration was developed in the 1980s and is still in use today. In the field of image restoration, research and application of diffusion models are reviewed, and this article provides a summary of the development history, methodology principles, and application cases associated with these topics. This article provides an introduction to the fundamental ideas and principles underlying diffuse models, as well as a summary of the current state of research and an outlook on potential future trends and prospects pertaining to image repair within the domain of image processing.

Keywords. artifacts repair; diffusion models; image restoration; digital image processing

1. Introduction

The field of digital image processing and computer vision has seen rapid advancements in recent years, which has led to the widediffusion adoption of image editing software in a variety of different application areas. Image repair is the process of restoring, reconstructing, or filling in missing, damaged, or noisy images by using the information contained within the image itself. The goal of image repair is to improve image quality and visual sensation.

At the same time, the Denoising Diffusion Probabilistic Model is a generated model that is used to generate new data samples, such as images, audio, text, and so on. This can be accomplished by using the model's output to generate new data. The output of the model can be used to generate new data, which is one way to achieve this goal. In addition to carrying out iterative diffusion and reverse diffusion operations, the diffusion model generates new samples by superimposing a random noise pattern on top of an already existing data sample. This process is known as diffusioning. To serve the purpose of serving the purpose of generating new samples by controlling the noise that is present

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in the data sample, the purpose of a distributed generating model is to serve that purpose. This is the primary thought process that underlies the model. In the course of the diffusioning process, noise will be gradually dispersed across the entire data sample. As a direct consequence of this, the distribution of the sample will become gradually more realistic and even as the process moves forward. The purpose of the reverse diffusion operation is to generate a new sample that is more representative of the real world by diffusioning the sample that was generated back to the original sample space in the opposite direction. This is accomplished through the process of diffusioning the sample back to the original sample space in the opposite direction.

Researchers have begun paying more and more attention, over the course of the past few years, to the concept of combining image repair and dissemination models. New samples are produced by the diffusion-generated model through the combination of diffusioning and reverse diffusioning operations, as well as the introduction of random noise. This method of generating, in contrast to conventional artifacts repair methods based on rules or images, automatically learns complex artifact repair patterns and generates repair effects that are both highly realistic and diverse. The diffusion-generation model can simultaneously make full use of large amounts of relic restoration data for training, which ultimately results in an improvement in the restoration effect's accuracy and stability. Furthermore, this model has the potential to revolutionize the field of artifact restoration by significantly reducing the time and effort required for manual repairs. Its ability to learn and adapt to different types of damage makes it a valuable tool for preserving historical artifacts for future generations.

Methods of image restoration that are based on distribution also have important application values in the field of conserving museums and cultural heritage. A variety of image flaws, such as the effects of aging, pollution, cracks, and other similar flaws, frequently impede the preservation and presentation of cultural heritage. These defects present a challenge to museum professionals. Image repair methods that are based on dispersive models have the potential to help restore damaged images that are part of cultural heritage, improve the visual quality of those images, and enhance the display effects of those images, all of which will contribute to the preservation and transmission of cultural heritages.

However, image repair methods that are based on diffusion models are not without their share of difficulties and challenges. For instance, questions like "how to choose the right diffusion parameters" and "how to deal with border conditions" still call for extensive research to be conducted. Second, dispersion-based image repair methods may have some limitations when dealing with complex image damage and require further improvement and optimization. These methods are currently under development. In addition, the computing efficiency and real-time performance of dispersion-based image repair methods may be limited in practical applications; consequently, there is an urgent need for more efficient algorithmic implementations.

This article will focus on image repair techniques that are based on diffuse models and will investigate the current state of research as well as the potential future applications of these techniques in the field of image processing. The fundamental ideas and guiding principles behind image repair and dissemination models will first be presented, followed by a discussion of the evolution of research that is pertinent to the topic. After that, we will concentrate on image repair methods that are based on diffusion models. These methods will include key issues such as the application of mathematical modeling to the diffusion process, the management of border conditions, and the selection of diffusion parameters. Following that, it will discuss the various applications of image restoration based on diffusion models in a variety of fields, such as the removal of image noise in computer vision, the recovery of images, and the restoration of images utilized in the preservation of cultural heritage.

2. Progress of Development

2.1 Historical evolution of the Generate model

In the 1940s and 1950s, someone came up with the idea of the Markov chain[10].The concept of the Malkov chain, which is used to describe the process by which the state of a random sequence is transferred from one iteration to the next, was first proposed by the Russian mathematician Andrei Markov[1].The Markov chain was the stepping stone that led to the development of diffusion-generation models in the years that followed.

The study of random processes[7] became popular in the 1960s and 1970s.Mathematicians started looking into random processes and random models in greater depth, including random walking and Brown movements, which laid the theoretical groundwork for the creation of diffuse-generated models[1].

The Shymarkov model[2] was initially proposed in the 1980s and again in the 1990s.The Hidden Markov Model, also known as the HMM, is a model that was initially developed by the American scientist L. L. Welch and is based on the Malkov chain. L. Rabiner was first presented to the public in 1986.HMM is utilized in a wide variety of fields, including speech recognition, natural language processing, and others, and it serves as a source of direction for subsequent diffusion-generation models.

The decade of the 2000s saw the rise of deep learning. Generating models have made significant progress in the fields of image processing, audio processing, and natural language processing as a direct result of the rapid development of technology based on deep learning. Deep-generation models[4], such as generating counter-networks (GANs) and variable self-coders (VAEs), have seen widediffusion application in the investigation of diffuse generating models, which has resulted in the opening of new doors for the creation of diffused generated models.

Among these, the DDPM[1] was developed as a model that is based on a diffusion process. It was first proposed in 2017 by Vahdat and colleagues. Images are produced by DDPM through the introduction of noise and the execution of a multi-stage diffusion process. This is accomplished through the learning of the conditional probability distribution that occurs during the diffusioning process. After that, the researchers worked tirelessly to enhance and perfect the DDPM by, among other things, employing a variety of noise models and enhancing the steps and parameter settings of the dispersion process. As a consequence of their efforts, a wide variety of research results were produced in the fields of image generation, noise reduction, and repair.

In a similar way, the DSM [3] is used as a generative model based on score matching. This model was originally proposed in 2010 by Vincent et al. The DSM creates images by first learning the scoring function of the image, which can be interpreted as modelling the gradient of the pixel values of the image. This allows the DSM to produce images with a high degree of accuracy. To achieve image noise reduction and generation, the DSM generates new image samples by minimising the negative gradient of the scoring function. This reduces the amount of negative gradients in the score function. The researchers have since worked tirelessly to enhance and extend the DSM in various ways, including incorporating combinations of deep neural networks and various other generative models. As a result of their efforts, a variety of research results have been generated in the field of image generation and image processing.

According to Figure 1 it can be seen that the use of diffusion generative models in the museum heritage restoration business dates back to the early 21st century. During this period, along with advances in computer technology, various technological processes, such as image processing and computer vision, were gradually applied to the restoration process of cultural objects. In the field of museum artefact restoration, diffusion-generating models have begun to be introduced as a computer vision-based restoration method. These models are used to simulate the processes of change that occur in time and space for cultural objects.

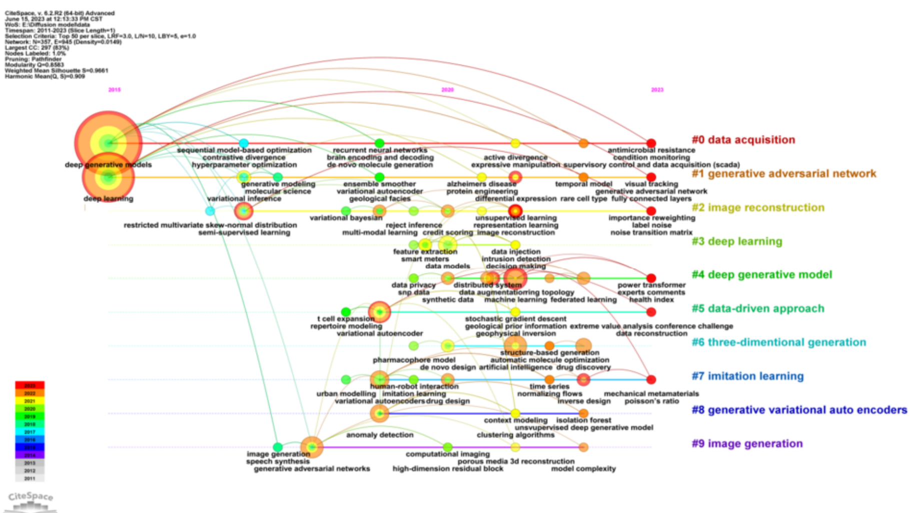

Figure 1. Research developments in generative modelling between 2011 and 2023

2.2 The evolution of Heritage Restoration

The restoration of cultural heritage[15] is an essential part of the field of cultural heritage protection, and its origins can be traced all the way back to ancient times.People in ancient civilizations used a variety of materials and techniques, such as welding metal, carving wooden sculptures, and sculpting stone. This allowed them to repair damaged artifacts. The field of restoring cultural relics has undergone significant development in recent years as a direct result of the application of digital technologies, which has contributed significantly to the advancement of science and technology in general.

Traditional techniques for repairing relics relied primarily on manual repair and chemical repair at the beginning of the 20th century. These techniques included cleaning the surfaces of relics, repairing missing parts, repairing damaged parts, and a number of other procedures[16]. It is possible for these techniques to restore damaged artifacts to some degree; however, there are a number of drawbacks associated with their use. Some of these drawbacks include the following: the restoration effect is difficult to achieve, the process of repair may cause additional damage to the artifact itself, and the repair process itself may be challenging to duplicate.

Around the same time that computer-assisted repair[17] technologies were first being introduced into the field, specialists in the field of repairing cultural relics were also beginning to implement these technologies[18]. Digital scanning, three-dimensional modeling, and virtual reality are some examples of the computer-assisted repair technologies that are currently available. These technologies are able to perform non-contact detection and analysis of artifacts, which can then be done before the relics are repaired. This enables the repair personnel to carry out repair operations with a higher degree of precision. In addition, digital technologies can be utilized in order to visualize the effects of repair, as well as to preserve and pass on the process of repair.

According to Figure 2 it can be seen that in recent years there has also been a boom in the use of model generation techniques[5] in the field of heritage restoration, which is an advanced form of artificial intelligence technology." Diffuse generative models are an important type of generative model that possess unique benefits. These benefits can be trained by including random noise to produce high quality relic restoration results. In addition, diffuse generative models make full use of the large amount of relic restoration data available to improve the accuracy and stability of restoration results. This new approach to heritage restoration enhances and extends the application of traditional heritage restoration methods. As a result, the field of heritage restoration is faced with new opportunities and challenges.

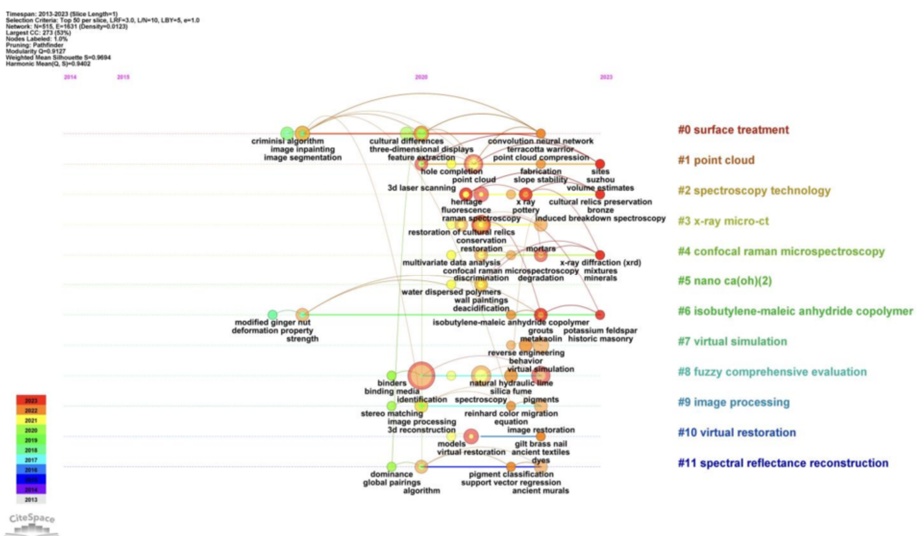

Figure 2. Research developments in heritage image restoration between 2013 and 2023

3. Analysis of Situation

3.1 Comparison of Diffusion Models

As can be seen in Figure 3, a number of typical approaches have emerged in the modelling field in recent years, including generative inverse networks (GAN), variable autocoding (VAE), flow-based models and diffusion models.

GAN[6] is a model that is composed of generators and judges. The generators are responsible for producing realistic data, and the judges are responsible for continuously optimizing the confrontation that occurs between the generators and the judges. GAN training allows generators and differentiators to gain knowledge from one another, which ultimately leads to an improvement in the overall quality of the generated samples. To train a generated model in such a way that it maps the potential variable z of random sampling to the probability distribution of the training set is the goal of the VAE[16] technique. The model that was generated by the VAE can be used to generate new data samples in addition to restoring the input sample data by generating the nebulous variable z.Flow-based Unbalanced thermodynamics has an impact on models by defining the Markov chain of diffusion steps, which gradually adds random noise to data. The model then learns the reverse diffusion process in order to construct the required data samples. The diffusion model, in contrast to the VAE model and the flow model, is learned using a predetermined process, and the hidden space z has a higher dimension.

The field of diffusion models[8] is currently undergoing a period of rapid development. Recent advancements in the training technology of this field have made it possible for diffusion models to be directly utilized for downstream tasks, which span the stage of modeling in the field of GAN.As a result of the ongoing growth and refinement of technological capabilities. In comparison to the GAN, the diffusion model[1] offers a higher degree of adaptability. It does this by gradually adding gas noise to the training data, and it also gradually removes the details of the original data, turning it into pure noise in the end. This destroys the training data. After that, by training the neural network, the entire process of destruction is turned around, gradually removing the noise, and ultimately producing images of a high quality. In the future, the process of the diffusion model will include a complex image data input model. This will be followed by a series of calculations known as the incremental operations, which will convert the input data from an orderly low-cutting state to an unorderly high-canning state, ultimately resulting in the generation of noise data. The forward process uses a normal distribution to define the transfer probability distribution. This normal distribution achieves minor changes in the data through the continuous addition of gas noise. In contrast to the forward process, the reverse diffusion process accomplishes the goal of reducing noise by performing a series of calculations that gradually transform noise data into other types of data, such as images. This is done in contrast to the forward process. The backwards process is also a Malkov chain[9], and its combined probability distribution can be estimated by using the known forward probability transfer distribution in combination with the unknown backwards probability transmission distribution. A conditional probability distribution is used to estimate the reverse probability transfer distribution in a diffusion mode[10], and it is assumed that this distribution follows the normal distribution. After training a neural network to obtain the correct parameters, an original image can be reconstructed based on the probability distribution of known conditions. Since each step in the process of going backward is unknown, this requires the use of a neural network to obtain those parameters.

The diffusion model performed tests using the ImageNet dataset at a variety of resolutions, which led to reduced Frechet Inception Distance (FID) values. Recent studies have shown that combining a classifier with an upper sampling diffusion model can further reduce FID values. This demonstrates that diffusion models have excellent performance in the generation of high-quality images and provide more opportunities for improving the quality of data generation and sample generation in practical applications.

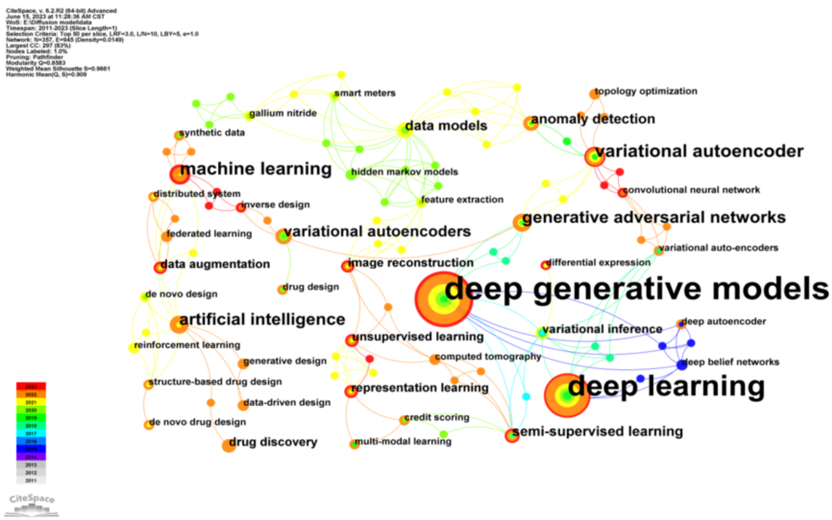

Figure 3. Research focus on generative models in recent years

3.2 Rescue Virtual Repair Technology Routes Based on Digital Image Repair Technologies

In the field of heritage conservation, digital image restoration technologies[19], when combined with other computer technologies already in use, have the ability to build virtual data information that can satisfy visual needs and restore the heritage's original visual effects. Digital image repair techniques can use computer technology to analyze data information on heritage, build heritage predictive models, and use image data to estimate the residual factor area to digital virtually repair of heritage, whereas traditional methods of heritage repair have some limitations. This technology has the potential to cut down on the amount of time needed for repairs[20], as well as reduce the amount of secondary damage that is caused to artifacts.

3.3 Application of Digital Image Restoration Technologies in the Conservation of Cultural Heritage

According to Figure 4 it can be seen that digital image restoration techniques used in conservation work are applied in the virtual restoration of heritage monuments. Due to historical and environmental factors, fallen or preserved artefacts may contain various pathogens such as mould and cracks. These factors may have contributed to the condition of the artefacts. Not only do these problems make appreciating the artefacts a challenge, but they also have the potential to lead to loss of information and misdirected research. In the past, techniques such as cleaning and painting have often been used to restore artefacts. However, this required a high level of artistry and practical experience from the restorer, and the different professional qualities of restorers could lead to differences in restoration results. However, with the help of digital image restoration techniques, cultural objects can be restored digitally and virtually by using computers to analyse data information about the objects, build predictive models and use the image data to estimate the area of residual elements. By taking this approach, the restoration cycle can be accelerated, errors caused by manual restoration can be avoided and secondary damage to the artefacts can be mitigated.

While the number of academics who study image restoration has grown steadily over the past few years, relatively little research has been done on how image restoration can be applied to the field of relics restoration, according to the findings of recent studies published in academic journals. Nevertheless, there have been some academics who have proposed some alterations. For instance, in 2021, four researchers, one of whom was Jooyoung Choi, proposed a method of generating based on a given reference image. They called their idea the DDPM Generation Process Guiding Method (ILVR)[5], and their goal was to generate images of a high quality. In the year 2022, a group of eight academics, one of whom was Zheng Haiti, came up with a solution to the problem of the difficulty in generating rational image structures when processing complex images by proposing a method they called CM-GAN. This method offered an efficient network structure for the GAN to use in image repair. In addition, Alex Nickel and a number of other researchers demonstrated, in a study that was conducted in 2021, that DDPM could be made to be competitive with its counterparts while still maintaining a high level of sample quality. Within the scope of their research, Muhammad Noruzzi and others developed a structure for translating images that was predicated on conditional diffusion models. In the study, Noruzzi and others revealed the impact of L2 and L1 loss on sample diversity in de-noise diffusion targets[13]. Additionally, through empirical studies, they demonstrated the importance of self-focus in neural architecture.

The challenge of image painting also saw significant progress with the advent of convolutional neural networks (CNN). Existing methods, on the other hand, have a few drawbacks when it comes to interacting with various kinds of models, and their overall performance is significantly hindered when they come into contact with invisible models. Based on the LaMa image painting framework, the author Lucero proposed a straightforward and all-encompassing method that he referred to as GLaMa as a means of resolving this issue. The stability of the model is improved by GLaMa by introducing additional types of models, each of which is better able to capture a different kind of missing information.

The research paper titled "Lion: Variable Automatic Encoder (VAE) for 3D shapes" presents a novel model for the generation of three-dimensional shapes called the LION. This model is founded on a variable automatic encoder that is used for layered potential spaces.It offers a powerful tool for digital artists because it can be utilized for activities such as multi-modular shape noise removal, material condition synthesis, and text- and image-driven 3D generation. In the meantime, the study report titled "RePaint: A Noise Dispersion Probability Model (DDPM) based on a painting method" proposed a new method called "RePaint," which is used to add new content to an image within a specified area of any binary masking. This method is referred to as "painting." This method regulates the generating process by sampling only the unblocked areas in the reverse diffusion iteration. A pre-trained unconditional DDPM is used as a generating precursor in this method. The model is able to generate high-quality and diverse output images because the technology does not modify or adjust the original DDPM network itself. These images are suitable for use with all different kinds of masks. There have also been studies that have concentrated on the implementation of decentralized noise dissipation probability models in the process of relics restoration. For instance, Jacob Austen and others proposed a discrete model of noise dispersion probability based on excess matrix selection. This model has the potential to improve the results of repairs in image and text fields.

In the field of restoring digital heritage[21], researchers have also proposed a number of novel approaches. For instance, Wang and other individuals scored the scores of the Jacobian reverse diffusion model of the micro renderer in 2022. They also identified technical challenges and proposed new estimate mechanisms to address these challenges. It was discovered by Gérard Paul and other researchers that diffuse models have a significant amount of potential in the field of image generation. These models even outperform GAN in terms of generating diversity, and the quality of the images that they produce is quite high. However, their research is restricted to three-dimensional shapes that are embodied as points or bodies, neither of which can accurately represent three-dimensional surfaces. As a result, they proposed a dispersed model of 3D shaped neuroscientific representation that operates in the potential space of an automatic decoder. This model creates a diverse and high-quality 3D surface by running in the potential space of the automatic decoder. Some studies also concentrate on displaying and visualizing digital artifacts collections as part of their research. For instance, in 2019, Lisa Jago and others pointed out that the expansion of digital relics collections provided many opportunities for access to cultural heritage. They also proposed a framework for the digitalization of heritage collections to display these relics in interactive software. Lisa Jago and others also pointed out that the expansion of digital relics collections provided many opportunities for access to cultural heritage. Additionally, they developed two pieces of software in order to try out and test the 3D models that were generated. It is possible to obtain high-resolution models with a low number of polygons by applying this framework, and then visualize those models using a variety of different devices.

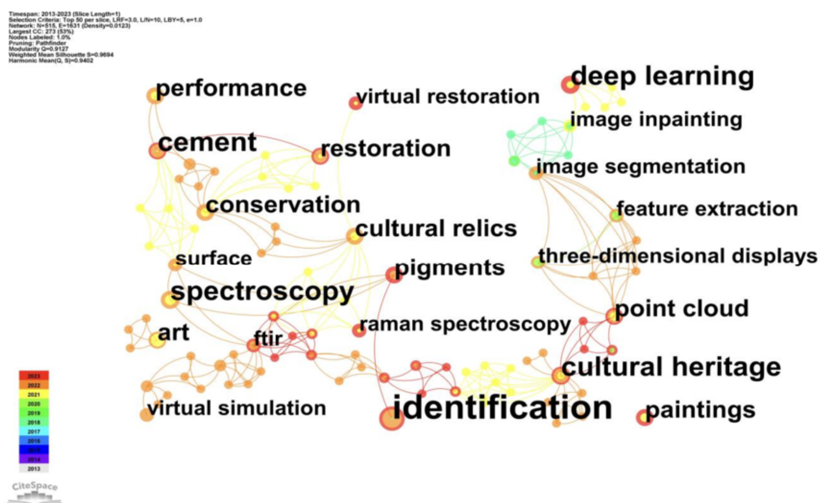

Figure 4. Research priorities for image restoration of cultural heritage in recent years

3.4 Analysis of Cases

Reconstructing the Bamian Buddha in Afghanistan required the use of mathematical image repair technology, which was provided by the German repair team[11].They gathered what was left of the Buddha's stones and used a technology that repairs mathematical images to repaint Buddha images. In this way, they were able to successfully recreate the image of Buddha by creating mathematical models in virtual space. In the meantime, the University of Beijing in China has teamed up with the University of Chicago and the Seychelles Museum in Washington, D.C. in order to collect the shattered hands and legs of the statue of the Buddha in order to examine them alongside the other Buddha statues already housed in the museum. They layered the different components of the Buddha image and used digital information to supplement the overall composition of the relics. This was accomplished through the use of digital image repair techniques. They were able to successfully repair the artifacts by employing a method that involved only partially controlling the whole physical. A broken statue of Adam that was on display at the Metropolitan Museum of Art needed to be fixed, which led to a situation very similar to the one described above. They began by performing a digital scan of the damaged area, and then proceeded to repair the marble statue by utilizing three-dimensional modeling in addition to other techniques. The statue of Adam was finally put on display after 12 years of labor and preparation. The entire process of restoring the relic was documented by the Metropolitan Museum, which resulted in the creation of a technical documentation that went on to become one of the most important classical cases in the field of relics restoration. The restored relic, which is now housed in a specially designed glass case, has become a popular attraction for visitors to the museum. It serves as a testament to the skill and dedication of the restoration team, as well as the enduring cultural significance of ancient artifacts[12].

4. Problems and Challenges

Traditional techniques for repairing artifacts involve having skilled professionals perform the manual work. However, this approach has a number of drawbacks, including the need for a high level of professional expertise, the fact that it is time consuming, and the fact that it is only applicable to relics. Combining image repair technologies[14] with diffuse generating models has introduced both new opportunities and new challenges to the field of relics repair in recent years due to the rapid development of computer vision and deep learning technologies.

The image restoration aspect of relic restoration, combined with the diffusion-generation model, faces the problem of the diversity of relics. Cultural relics as the carrier of history and culture, their form, materials, colors and other aspects of diversity make the restoration of cultural relics there is a greater difference. Different artifacts may require different methods and techniques of restoration, so how to apply a diffusion-generated model to different types of artifact restoration and satisfactory restoration results remains a question to be addressed.

The assessment of image repair presents its own unique set of challenges. An objective evaluation of the effect that the repair has had on the relic is essential because the goal of relic restoration is to restore the relic to as close to its original state as possible while also maintaining as much of its historical significance as possible. On the other hand, the evaluation criteria for the restoration of relics are frequently subjective, dependent on the expert judgment of the personnel who are performing the repairs, and difficult to quantify and standardize .In order to confirm the logic and acceptability of the repair effect, more research and investigation into techniques that can objectively evaluate the repaired images that the diffusion-generated model has generated is still necessary.

The training procedure for the diffuse model is difficult to understand and requires a significant amount of calculation, and it also presents a challenge .Generating counter-networks (GANs) and variable self-coders (VAEs) are two important representatives of distributed generating models. The training processes for these models frequently require large quantities of samples and computing resources, and the models are susceptible to issues such as training instability and pattern collapse. In order for this method to be better applied to the field of heritage restoration, additional research and optimization work needs to be done on how to solve the problem of ensuring the stability and effectiveness of dispersed generating models during the training process.

Last but not least, the restoration of relics involves many different aspects such as ethics, law, and culture, all of which should be taken into consideration. Artifacts are an important part of cultural heritage, and the process of restoring them involves many different facets, including culture, ethics, and the law. When using a diffuse-generated model to restore artifacts, it is necessary to take into consideration a variety of factors, including the legitimacy, authenticity, historical value of the artifacts, and so on. This is done to ensure that the results of the repair do not cause the authentics or historical values of the relics to be compromised in any way. When applying the diffusion-generation model, it is necessary to fully consider the standards and methods of restoration in different cultures in order to avoid cultural conflict and controversy. This is because there are differences in the perception of and requirements for the restoration of heritage in different cultural contexts. In addition, the restoration of heritage involves consideration of cultural diversity.

The implementation of diffusion generation models in the field of heritage restoration presents a number of difficulties and obstacles; however, it also paves the way for the development of new opportunities in the field of heritage restoration. By analyzing large amounts of relic image data, distributed generating models are able to generate restorative images that are highly authentic and artistic. This provides a new auxiliary restoration approach to the process of relic restoration. Diagrams of repairs that were generated through the diffusioning of generated models. In addition, distributed generating models have the capacity to carry out virtual restoration experiments in the field of heritage restoration. The goal of these experiments is to cut down on the dangers that are actually associated with restoring heritage and to safeguard important cultural artifacts.

5. The Future Prospect

There is a tremendous amount of untapped potential in the field of relics restoration when diffuse generating models are applied. It is possible for future research to investigate a variety of topics, such as the restoration of various kinds of artifacts, the objective evaluation of the effects of restoration, the optimization of training in diffuse generating models, and the consideration of ethical, legal, and cultural factors. Diffuse generation models are anticipated to play a more important role in the field of heritage restoration, making greater contributions to heritage conservation and inheritance as a result of ongoing research and innovation. In subsequent research, the training algorithms for diffusion-generated models can be further developed and improved, the process of training the model can be sped up, and both the variety and quality of the samples that are generated can be improved. Additionally, future research directions include the combination of other advanced machine learning and artificial intelligence technologies, such as deep-intensified learning and counter-generating networks. These advancements can further enhance the accuracy and efficiency of the model, allowing it to handle more complex tasks and generate more realistic samples. Furthermore, the integration of these technologies can lead to the development of more sophisticated applications in various fields such as gaming, art, and medicine.

6. Conclusion

Diffusion generating models have achieved good generating effects in the fields of image generation, image repair, and image synthesis through the use of simulated diffusion processes. These models also demonstrate their one-of-a-kind advantages in a few specific application scenarios. Nevertheless, distributed generating models continue to face a number of obstacles and difficulties. For instance, the process of training is rather sluggish, the training of the model is unreliable, the variety of samples that are to be generated needs to be improved, and the control of image details is somewhat restricted. In the not-too-distant future, it is possible that diffuse generating models will develop more effective algorithms, more stable training, a broader range of applications, more powerful generating and control capabilities, and the ability to combine with other technologies. Furthermore, advancements in artificial intelligence and machine learning may lead to more sophisticated and realistic image generation, allowing for even greater creativity and innovation in fields such as entertainment, advertising, and design. As these technologies continue to evolve, the possibilities for image generation are endless.

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