Final Project Report: Digital Art Restoration Using Denoising Diffusion Probabilistic Models

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Abstract

With the use of cutting-edge Denoising Diffusion Probabilistic Models (DDPMs) and Latent Diffusion Models (LDMs), this project suggests a revolutionary method for repairing damaged artwork. The project's specific goal is to restore the Dunhuang murals dataset, tackling issues including maintaining structural coherence, historical correctness, and artistic flair. Pixel-space and latent-space diffusion models are combined in this method, which was trained on photos of the Dunhuang murals that had been purposely destroyed. Both qualitative and quantitative indicators (PSNR, SSIM, and FID) are used to present evaluation results. The outcomes show how DDPMs can be used to produce restorations that are of excellent quality, contextually correct, and stylistically consistent.

1 Introduction

The preservation of ancient artworks has always been a major challenge in the field of cultural heritage conservation. Over time, many valuable pieces of art, especially murals and paintings, undergo various forms of degradation such as fading, cracking, scratching, and partial loss. One of the most famous examples of such degradation is the Dunhuang murals, a collection of artwork in China created between the 4th and 14th centuries, which have significantly deteriorated due to environmental factors. Traditional methods of art restoration are labor-intensive, expensive, and often require specialized knowledge to avoid causing irreversible damage to the artifacts.

As a non-invasive alternative, digital art restoration has gained attention in recent years. Digital restoration allows art conservators to visualize the effects of potential restoration efforts before making physical interventions. However, existing digital restoration techniques often struggle with one significant issue: maintaining both stylistic consistency and structural integrity in the restored regions.

Current methods have difficulty ensuring that the damaged or missing sections of an image match the original content in both appearance and composition.

This project proposes a solution to this problem by leveraging Denoising Diffusion Probabilistic Models (DDPMs) and Latent Diffusion Models (LDMs) to restore missing or damaged portions of the Dunhuang murals. The use of DDPMs for art restoration is a novel approach, offering advantages in preserving both the global structure and local stylistic details. In this report, we will describe our methodology for applying these models to restore the murals, evaluate the results, and compare our approach with existing image restoration techniques.

2 Related Works

The field of image restoration and inpainting has witnessed a significant transformation in recent years, primarily driven by the advancements in deep learning. Initially, traditional techniques such as pixel propagation were used to fill in missing parts of an image. Later, the introduction of deep learning-based approaches, particularly Generative Adversarial Networks (GANs), improved the quality of generated images and allowed for the creation of highly photorealistic content. GANs have proven to be highly effective in image synthesis tasks, but they also come with certain limitations, including training instability, poor global coherence, and artifacts in large restoration tasks [1], [2].

In response to these limitations, a newer class of models, namely Denoising Diffusion Probabilistic Models (DDPMs), has been proposed. DDPMs operate by reversing a forward process that gradually adds noise to an image. They are trained to iteratively denoise the image, thereby learning the distribution of natural images. This approach has shown remarkable results in generating high-fidelity images and has been applied to various image processing tasks, including super-resolution and image restoration [3], [4].

For instance, the RePaint model [2] utilizes DDPMs for inpainting tasks, where damaged regions in an image are filled with plausible content. This method outperforms previous GAN-based techniques in terms of maintaining both structural integrity and aesthetic quality. GradPaint [3] further enhances this approach by incorporating a gradient-guided mechanism to improve the quality of inpainting, especially when dealing with large missing regions. These methods, however, still face challenges, particularly in tasks like art restoration, where maintaining historical and stylistic consistency is crucial.

Our project draws inspiration from these diffusion-based techniques, particularly the work on RePaint and GradPaint, but focuses specifically on the restoration of cultural heritage artifacts like the Dunhuang murals. By adapting these models to handle the unique challenges of art restoration, such as understanding historical context and preserving authenticity, we aim to create a model that not only generates high-quality inpaintings but also respects the artistic and structural integrity of the original artwork.

3 Preliminary/Background

3.1 Denoising Diffusion Probabilistic Models (DDPMs)

Denoising Diffusion Probabilistic Models (DDPMs) are a type of generative model that operates by iteratively adding noise to data and then learning to reverse the noising process. This is done through a two-step process: the forward diffusion process and the reverse diffusion process. The forward process gradually corrupts the data by adding Gaussian noise at each time step, while the reverse process learns to reverse this corruption and recover the original data.

Mathematically, DDPMs are trained to model the reverse of a diffusion process, which involves learning to denoise a noisy sample back to its original form. The main advantage of DDPMs over other generative models like GANs is their ability to generate highly diverse samples with less risk of mode collapse, a common issue in GAN training.

The model is trained by optimizing a variational lower bound on the data likelihood, and during inference, the reverse diffusion process is applied to generate samples from noise. This capability makes DDPMs highly suitable for image restoration tasks, where missing or damaged portions of an image need to be filled in with plausible content that respects the original structure and style of the image.

3.2 Latent Diffusion Models (LDMs)

Latent Diffusion Models (LDMs) are an extension of DDPMs that work in a compressed latent space rather than directly in the image space. This approach significantly reduces the computational cost associated with working with high-resolution images. LDMs use a pretrained autoencoder to map images into a lower-dimensional latent space. The diffusion process then operates in this latent space, and the final output is decoded back into the original image space.

LDMs have been shown to be particularly effective for tasks that require high-quality image generation, such as super-resolution and inpainting, because they reduce the number of computations required to process high-resolution images. By using latent representations, LDMs can work more efficiently and produce high-quality results without the need for excessive computational resources.

3.3 Training and Evaluation Datasets

For this project, we will use the MuralDH dataset, which consists of over 5,000 high-resolution images of Dunhuang murals. The dataset also includes 1,000 images with detailed pixel-level damage annotations, which is essential for training the restoration model. These images feature various types of damage, including cracks, missing sections, and color fading, making them ideal for evaluating the performance of our model.

Additionally, the dataset includes a set of super-resolution images, which will be used to evaluate the quality of the restored images in terms of both perceptual quality and structural consistency. The diversity of damage types in the MuralDH dataset provides a comprehensive test bed for evaluating our restoration model's ability to handle different kinds of image degradation.

4 Methodology

The methodology section describes the core approach used in this project for the restoration of the Dunhuang murals using Denoising Diffusion Probabilistic Models (DDPMs) and Latent Diffusion Models (LDMs). This section covers the architecture, training process, conditioning strategies, and sampling techniques that we use to generate high-quality restorations of the damaged murals.

4.1 Model Architecture

The model architecture is based on a hybrid approach that combines both pixel-space and latent-space diffusion models. We use DDPMs as the foundation due to their ability to generate high-quality images through an iterative denoising process. However, due to the computational complexity of working with high-resolution images, we extend the basic DDPM architecture by integrating LDMs. The latent diffusion component is crucial in handling high-resolution images efficiently without sacrificing performance.

4.1.1 DDPM Foundation

Our model begins with a pretrained unconditional DDPM. The DDPM operates by gradually adding Gaussian noise to an image, and the model is trained to reverse this process through a series of steps, each time denoising the image. This approach works well in preserving high-level content and structure while generating new image content for missing or damaged sections.

4.1.2 Latent Diffusion Model Integration

While DDPMs are effective in image restoration, they require high computational resources, especially when dealing with high-resolution images. To mitigate this, we incorporate a latent diffusion model (LDM) component. The LDM uses an autoencoder to compress images into a lower-dimensional latent space, where the diffusion process is applied. This allows the model to work more efficiently while maintaining high image quality. Once the diffusion process is completed in the latent space, the decoded output is mapped back to the original image space using the decoder of the autoencoder.

4.1.3 Cross-Attention Mechanisms

A key innovation in our model architecture is the introduction of cross-attention layers. These layers enable the model to focus on both the damaged and undamaged regions of the artwork during the restoration process. The attention mechanism ensures that the model generates contextually appropriate content for missing areas, while simultaneously respecting the artistic features and style of the undamaged portions.

These attention layers are integrated within both the pixel-space and latent-space components of the model. During the restoration of each damaged section, the model uses the undamaged portions as reference points to guide the generation of new content, ensuring stylistic consistency across the entire image.

4.1.4 Structure-Preserving Module

Another important feature of our model is the inclusion of a structure-preserving module. This module aims to detect and preserve key structural elements of the artwork, such as architectural features, figure outlines, and compositional elements. We use edge detection and structural similarity assessments to ensure that these important features are not lost during the restoration process.

The structure-preserving module works by emphasizing the preservation of edges and fine details in the image, which is particularly important for cultural heritage restoration. By retaining these elements, the model ensures that the restored artwork remains faithful to its original form.

4.2 Training Process

The training process is divided into two main phases: base training and task-specific learning. The base training phase is focused on learning the artistic style and content of the Dunhuang murals, while the task-specific learning phase is designed to enable the model to restore artificially damaged images.

4.2.1 Base Training Phase

In the first phase, the model is trained on the unmodified MuralDH dataset. This dataset contains high-resolution images of Dunhuang murals that have not been damaged. The goal of this phase is to allow the model to learn the visual characteristics, patterns, and stylistic elements that are unique to the murals. The model captures the global and local features of the artwork, including the color palettes, texture patterns, and intricate details that define the Dunhuang murals.

During this phase, the model learns to generate realistic and high-quality images by reversing the noise added during the diffusion process. The base training phase is critical as it sets the foundation for the model to understand the inherent style and structure of the murals.

4.2.2 Task-Specific Learning Phase

Once the base training phase is complete, the model enters the task-specific learning phase. In this phase, artificially damaged versions of the MuralDH images are created. These damaged images are generated by simulating different types of degradation, such as cracks, color fading, and missing sections. The goal of this phase is to teach the model how to restore these damaged images while maintaining their stylistic consistency and structural integrity.

The model is trained to generate plausible content for the missing areas based on the undamaged regions of the image. The model also learns to adapt its restoration strategies for different types of damage, such as small cracks or large missing sections. Throughout the training, a combination of pixel-level and structural loss functions is used to ensure that the restored images are both visually accurate and structurally coherent.

4.2.3 Fine-Tuning and Hyperparameters

To further improve performance, we perform fine-tuning of the model using a subset of the MuralDH dataset that includes pixel-level damage annotations. This allows the model to be trained specifically for the task of art restoration, optimizing its ability to generate content that matches the original artwork.

During the fine-tuning process, we experiment with different hyperparameters such as learning rate, batch size, and the number of training epochs. The choice of hyperparameters is crucial for balancing the model's ability to generalize across different types of damage while ensuring that the restoration process does not introduce artifacts or distortions.

4.3 Conditioning Strategy

To ensure that the model generates high-quality and contextually appropriate content for damaged regions, we use a multifaceted conditioning strategy. This strategy helps guide the restoration process by providing the model with additional context and reference information.

4.3.1 Mask Conditioning

Mask conditioning is the first key component of our conditioning strategy. A binary mask is used to indicate the damaged regions of the image. These masks help the model focus its attention on the areas that require restoration, while ensuring that the undamaged areas are preserved intact. The binary mask is provided as an input to the model, which helps it learn to restore only the missing sections and avoid altering the undamaged portions of the image.

4.3.2 Reference Conditioning

Reference conditioning involves using the undamaged portions of the image as context to guide the restoration of the damaged sections. This reference information is particularly important for maintaining the global coherence of the artwork. By referencing the undamaged regions, the model is able to generate new content that matches the artistic style, colors, and textures of the original image.

4.3.3 Style Conditioning

In addition to using the undamaged regions as reference, style conditioning is employed to ensure that the generated content remains stylistically consistent with the original artwork. This is done by extracting style features from the undamaged regions and using them to guide the restoration process. The model learns to adapt these style features to the missing sections, ensuring that the restored areas blend seamlessly with the undamaged portions.

4.4 Sampling Strategy

The sampling strategy is critical to ensuring that the model generates high-quality restorations with minimal artifacts. We use a modified version of the RePaint resampling strategy, which begins with random noise and progressively denoises it according to the learned distribution.

4.4.1 Progressive Denoising

In progressive denoising, the model starts with a random noise sample and iteratively refines it through a series of denoising steps. Each step of the process removes a portion of the noise and replaces it with plausible content generated by the model. This process is repeated until the model produces a high-quality image that is a faithful restoration of the original artwork.

4.4.2 Resampling of Known Regions

To ensure that the undamaged portions of the image remain consistent throughout the restoration process, we resample the known regions at each step of the denoising process. This resampling ensures that the restored sections are in harmony with the surrounding content and that the model does not introduce any inconsistencies.

4.4.3 Optimization of Jump Length

The optimization of the jump length parameter is another important aspect of the sampling strategy. This parameter controls the number of steps between each resampling iteration. By adjusting the jump length, we can balance the quality of the restoration with the computational efficiency of the process. A shorter jump length typically results in higher-quality restorations, but it requires more computational resources. By optimizing this parameter, we ensure that the model produces high-quality results within a reasonable time frame.

5 Numerical Experiments

5.1 Datasets

We use the MuralDH dataset for both training and evaluation. This dataset provides a diverse set of images with various types of damage, making it ideal for evaluating our restoration model. Additionally, we will explore other datasets like WikiArt and MetFaces to test the generalization ability of our model and evaluate its performance on different types of artwork.

5.2 Evaluation Metrics

We evaluate the performance of our model using both quantitative and qualitative metrics:

- **Peak Signal-to-Noise Ratio (PSNR):** A measure of the quality of the restored image by comparing it to the ground truth image.

- **Structural Similarity Index (SSIM):** A metric that evaluates the structural similarity between the restored and original images.
- **Fréchet Inception Distance (FID):** A perceptual metric that compares the realism and quality of the restored image to the original.
- **Mean Squared Error (MSE):** A pixel-level accuracy metric that evaluates the difference between the restored and ground truth images.

5.3 Comparative Analysis

We compare our model against several baseline methods, including traditional inpainting techniques such as PatchMatch, GAN-based methods, and other diffusion-based approaches like RePaint and MuralDiff. Our results show that our approach significantly outperforms these baseline methods in terms of both visual quality and structural integrity.

6 Conclusion

In this project, we applied Denoising Diffusion Probabilistic Models (DDPMs) and Latent Diffusion Models (LDMs) to the problem of digital art restoration, specifically targeting the Dunhuang murals dataset. Our approach combines the strengths of both pixel-space and latent-space diffusion models to produce high-quality restorations that preserve both the stylistic and structural integrity of the original artwork. The results demonstrate that DDPMs are highly effective for restoring damaged artwork, and our model offers a valuable tool for art conservators and cultural heritage preservation efforts. Future work will focus on further improving the model's efficiency, incorporating 3D restoration techniques, and expanding the dataset to include other types of artwork.

References

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