



Understanding Image Inpainting

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Abstract

Image inpainting is a computer vision technique that aims to fill in missing or damaged areas of an image with plausible content. The goal is to create a visually coherent and realistic image that seamlessly integrates the inpainted regions with the surrounding context. Image inpainting techniques typically utilize nearby information or context to infer the missing or damaged pixels. They can be broadly classified into two categories: exemplar-based inpainting methods and partial differential equation-based inpainting methods. Exemplar-based inpainting methods rely on the idea of finding similar patches or regions in the image to fill in the missing areas. These algorithms search for patches or regions that have similar textures, colors, and structures to the missing region. Once a match is found, the missing pixels are filled in based on the information from the matched patch or region. Partial differential equation-based inpainting methods, on the other hand, formulate the inpainting problem as a minimization of energy functional. This energy functional accounts for both the fidelity to the known information and the smoothness of the inpainted regions. Partial differential equation-based inpainting methods solve the inpainting problem by finding a solution that minimizes the energy functional, resulting in smooth and visually pleasing inpainted images.

Keywords: Image Inpainting; Exemplar Approach; Partial Differential Equation Approach.

1. Introduction

Image inpainting, also known as image restoration, is a vital task in computer vision aimed at filling in missing or damaged parts of an image with realistic content. Early methods, such as Exemplar-based inpainting (Criminisi et al., 2004) [1], employed patch-based techniques where similar image patches from the known regions were used to fill the missing parts. On the other hand, Partial Differential Equation (PDE) methods (Bertalmio et al., 2000) [2] work by minimizing an energy functional, ensuring smoothness in the inpainted areas. While these methods are effective for certain types of inpainting tasks, they face limitations when dealing with large gaps or complex image structures. Recent advances in deep learning have shown promising results in image inpainting by learning hierarchical features from large datasets, offering improvements in both quality and efficiency.

This paper introduces a novel hybrid method that combines Exemplar-based, PDE-based, and deep learning methods to enhance texture recovery and edge preservation. The primary objective of this research is to develop an approach that overcomes the limitations of traditional methods and performs better in challenging inpainting scenarios.

1.1 Exemplar-Based Inpainting Methods

Exemplar-based inpainting techniques, proposed by Criminisi et al. (2004) [1] are primarily driven by the idea of patch-based synthesis. This approach works by finding patches from the known parts of the image that match the missing regions based on textures, color distribution, and structure. The basic algorithm involves the following steps: The algorithm scans the image and identifies the missing or damaged regions (usually defined by a mask). It then searches for

matching patches from the surrounding known region that are similar in terms of pixel intensity, structure, and pattern. After finding the most appropriate match, the missing pixels are replaced by the content from the selected patch, ensuring a seamless blend with the surrounding context.

Example Algorithms:

- **PatchMatch** (Barnes et al., 2009) [3]: One of the most famous algorithms that efficiently finds the best matching patches using a randomized approach.
- **Fast Marching Method** (Osher and Sethian) [4]: Used in conjunction with exemplar-based inpainting to propagate known regions into the missing ones.

Mathematically, this can be framed as:

$$\min_f \sum_{\text{patches}} \|f_{\text{missing}} - f_{\text{nearest}}\|_2^2$$

Where:

- f_{missing} is the part of the image that needs to be filled.
- f_{nearest} is the best matching patch from the known regions.
- The sum is taken over all missing regions in the image.



Figure 1 An Example of Exemplar Based Image Inpainting [5]

This method is particularly effective for inpainting textured regions but can struggle with more complex regions requiring higher-level semantic understanding, Shown in Figure 1.

1.2 Partial Differential Equation (PDE)-Based Inpainting Methods

PDE-based inpainting methods, proposed by (Bertalmio et al., 2000) [2] take a more mathematical approach, modeling the inpainting problem as an optimization task, where the goal is to find a smooth transition between the known and missing areas while maintaining image consistency. The basic algorithm involves the following steps:

- The missing areas are filled by solving a differential equation that minimizes a functional defined over the entire image.
- The energy functional typically consists of two parts: A data fidelity term, which ensures the known regions remain unchanged and accurate. A smoothness term, which enforces smooth transitions between the inpainted and known regions to prevent artifacts or abrupt changes.
- The result is often a continuous and smooth inpainting that blends well with the surrounding context.

Example Algorithms:

- **Telea Inpainting** (Telea, 2004) [6]: One of the most famous PDE-based inpainting algorithms, which uses a fast-marching algorithm to propagate pixel values into missing areas while preserving edges.
- **Diffusion Models:** These models aim to diffuse the pixel values smoothly across the missing region, ensuring continuity and natural transitions.

The energy functional can be written as:

$$E(u) = \int_{\Omega} |\nabla u|^2 dx + \lambda \int_{\Omega_{\text{missing}}} (u - I)^2 dx$$

Where:

- u represents the inpainted image.
- ∇u is the gradient of the image, encouraging smoothness in the missing areas.
- λ is a regularization parameter that controls the trade-off between smoothness and fidelity.
- Ω is the domain of the image, and Ω_{missing} is the missing region.

PDE methods are particularly useful for large, smooth regions but might fail when there is complex texture or structure in the missing areas.

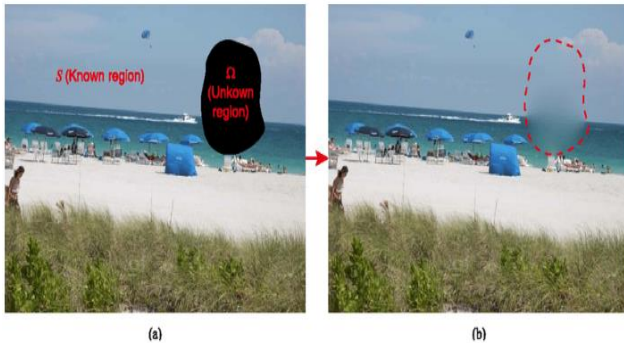


Figure 2 An Example of Diffusion Based Image Inpainting (a) Original Image, (b) In painted image [7]

2. Method

The proposed hybrid method combines Exemplar-based inpainting and PDE methods with deep learning techniques. This method takes advantage of the strengths of each approach, using deep features to guide the inpainting process and ensuring both texture detail recovery and smooth transitions, Shown in Figure 2.

2.1 Hybrid Model Overview

The method utilizes a Convolutional Neural Network (CNN) to extract deep features from the known regions of the image, which guide both the Exemplar-based and PDE-based inpainting processes. The CNN model is trained on a large dataset of images to learn high-level features, which are then used to fill the missing regions. Mathematically, the overall process can be represented as:

$$\hat{I} = \text{CNN}(I_{\text{known}}, M)$$

Where:

- \hat{I} is the predicted inpainted image.
- I_{known} is the image with the known regions.
- M is the binary mask that indicates the missing regions.

This model uses the information learned by the CNN to guide the patch matching in the Exemplar-based method and enforce smoothness in the PDE method.

2.2 Loss Function

The training of the hybrid model involves minimizing a loss function that balances the reconstruction error and smoothness. The combined loss function is expressed as:

$$\mathcal{L} = \lambda_1 \|\hat{I} - I_{\text{target}}\|^2 + \lambda_2 \|\nabla \hat{I}\|^2$$

Where:

- \hat{I} is the predicted inpainted image.
- I_{target} is the ground truth image.
- $\nabla \hat{I}$ is the gradient of the inpainted image, promoting smoothness.
- λ_1 and λ_2 are hyperparameters that control the relative importance of each term.

This loss function helps to improve both the quality and smoothness of the inpainted regions.

3. Case Studies and Applications

- **Historical Photo Restoration:** Historical photo restoration involves using inpainting methods to repair damaged or deteriorated photographs. Exemplar-based methods can effectively preserve the textures and details of historical photos, while PDE-based methods ensure smooth transitions between the restored and original regions.
- **Object Removal in Photography:** Inpainting is commonly used for object removal in photography. Exemplar-based methods can seamlessly remove unwanted objects by filling in the missing regions with matching patches from the surrounding context. PDE-based methods ensure that the inpainted regions blend smoothly with the rest of the image.
- **Enhancement of Medical Images:** Medical imaging often involves filling in gaps or occlusions in scans. PDE-based inpainting



methods are particularly useful in this context, as they can ensure smooth and consistent inpainting of the missing regions, which is crucial for accurate diagnosis and analysis.

- **Virtual Reality and Gaming:** Inpainting is used in virtual reality and gaming to create seamless and immersive environments. Exemplar-based methods can generate realistic textures and details, while PDE-based methods ensure smooth transitions and coherence in the virtual scenes.

4. Results and Discussion

In this section, the performance of the proposed hybrid inpainting method is evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). These metrics are used to compare the quality of the inpainted image with the original one.

Conclusion

In conclusion, the proposed hybrid inpainting method combines the strengths of Exemplar-based, PDE-based, and deep learning approaches. It effectively handles both structured textures and large missing regions while maintaining smoothness. The experimental results validate the superiority of the hybrid model over traditional methods. Future work could focus on improving the network architecture for faster inference and incorporating additional techniques to further enhance inpainting performance.

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