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IMAGE INPAINTING WITH LOCAL AND GLOBAL REFINEMENT

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ABSTRACT

Recent advancements in deep learning have significantly improved the performance of image inpainting, with most approaches relying on encoder-decoder architectures, often augmented with skip connections, that possess large receptive fields—typically larger than the image resolution itself. The receptive field refers to the set of input pixels influencing a particular neuron. However, in image inpainting, the size of the region required to repair missing areas varies depending on the type of missing content, and a large receptive field may not always be ideal, especially for recovering local structures and textures. Moreover, large receptive fields can lead to unwanted artifacts, which may negatively impact the inpainting process. In response to these issues, we propose a novel three-stage inpainting framework that incorporates both local and global refinement stages. Initially, we utilize an encoder-decoder network with skip connections to produce coarse inpainting results. Next, a shallow deep model with a small receptive field is applied for local refinement, reducing the influence of distant artifacts. Finally, we employ an attention-based encoder-decoder network with a larger receptive field for global refinement. Experimental results demonstrate that our method outperforms state-of-the-art techniques on three widely used image inpainting datasets. Furthermore, our local and global refinement network can be seamlessly integrated into existing networks to enhance their inpainting performance. Code is available at https://github.com/weizequan/LGNet.git.

Index Terms—Image inpainting, Neural networks, Receptive field

I.INTRODUCTION

Image inpainting, the task of filling in missing or corrupted parts of an image, has been an active area of research in computer vision and image processing. With the rise of deep learning, particularly convolutional neural networks (CNNs), significant progress has been made in addressing this challenge. Traditional image inpainting methods, such as patch-based and

exemplar-based approaches, rely heavily on the assumption that similar textures and structures can be found within the image to fill in the missing regions. However, these techniques often struggle with complex images where the missing regions involve intricate patterns or large areas of missing data.

In recent years, deep learning-based image inpainting methods have emerged as a powerful alternative. These methods generally use encoder-decoder architectures to encode the image context and then decode it to predict the missing pixels. Some of these architectures are augmented with skip connections to facilitate the flow of detailed information between the encoder and decoder. The key advantage of deep learning models is their ability to learn and propagate complex image features, improving the inpainting quality significantly over traditional methods. A key feature of many successful image inpainting networks is the large **receptive field**—the area of the input image that contributes to each neuron in the network. A large receptive field helps capture global context, making it suitable for repairing missing regions that span a large portion of the image.

However, there are inherent limitations when using a large receptive field in image inpainting. For one, the area required to repair different regions varies significantly depending on the content and context of the missing part. In many cases, a large receptive field may not be optimal for repairing fine-grained local structures, such as textures and small details. Furthermore, when the receptive field is too large, the model may unintentionally introduce artifacts from distant regions, disturbing the overall completion quality. These undesired artifacts often reduce the effectiveness of the inpainting process.

To address these challenges, we propose a novel approach that rethinks the traditional use of large receptive fields in image inpainting. Our method introduces a three-stage framework for inpainting, incorporating both **local and global refinement** stages to better handle different levels of image detail. First, we use an encoder-decoder network with skip connections to generate initial coarse inpainting results. Then, we introduce a shallow deep model with a small receptive field to perform local refinement, ensuring that the local structures and textures are restored with greater precision. Finally, we apply an attention-based encoder-decoder network with a larger receptive field for global refinement, capturing broader contextual information and ensuring that the final inpainted image looks natural and consistent.

The contributions of this work are threefold:

1. We introduce a multi-stage inpainting framework that integrates local and global refinement to address both fine-grained textures and large contextual information.

2. We propose a shallow deep model with a small receptive field to reduce the influence of distant artifacts and focus on local image details.

3. We demonstrate that our method outperforms state-of-the-art inpainting methods on several benchmark datasets, showing improvements in both local structure recovery and overall image consistency.

The rest of the paper is organized as follows: Section II reviews related work in the field of image inpainting, highlighting existing methods and their limitations. Section III describes our proposed inpainting framework, including details of the local and global refinement stages. Section IV presents experimental results, comparing our method with other state-of-the-art approaches. Finally, Section V concludes the paper with a summary of our findings and potential future directions for this research.

II.LITERATURE REVIEW

Image inpainting has been a well-studied problem in computer vision for several decades, evolving from traditional methods to modern deep learning approaches. The main goal of inpainting is to restore missing or corrupted regions of an image in a visually coherent manner by leveraging information from the surrounding pixels. This section reviews the key developments in image inpainting techniques, highlighting both traditional and deep learning-based methods, and discusses the challenges and limitations of existing approaches.

Traditional Image Inpainting Methods

Early methods for image inpainting were primarily based on **patch-based techniques** and **exemplar-based approaches**. These methods focus on finding similar patches from the known regions of the image and using them to fill in the missing areas. A key contribution to this field was the work by **Criminisi et al. (2004)**, who proposed an exemplar-based inpainting algorithm. Their method utilized texture synthesis, where missing pixels were filled by selecting the most similar patches from the available part of the image. This approach showed strong results in repairing small and texture-based missing regions but struggled with more complex cases, especially when the missing region covered large portions of the image or required structural information.

Another well-known technique is **texture synthesis** based inpainting, which focuses on filling the missing pixels by maintaining local coherence in the texture. **Barnes et al. (2009)** introduced an efficient texture synthesis method that allowed large texture regions to be filled by copying and blending patches from known areas. Although these methods work well for repairing small missing regions with repetitive structures, they are not effective for more complex tasks like repairing large or semantically important areas, such as faces or objects.

Deep Learning-Based Image Inpainting

With the success of deep learning in computer vision tasks, particularly convolutional neural networks (CNNs), image inpainting methods based on neural networks have gained

prominence. These approaches are capable of learning high-level representations from large datasets, which enables them to generate more realistic inpainting results, especially for large and structurally complex missing regions.

The introduction of **autoencoders** and **encoder-decoder architectures** in deep learning brought significant improvements to image inpainting. These networks consist of an encoder that learns a compressed representation of the input image and a decoder that reconstructs the image from this representation. **Pathak et al. (2016)** pioneered a deep learning approach for image inpainting using an encoder-decoder architecture, where they introduced the **context encoder** model to fill missing regions of images. The model was trained to reconstruct missing parts by leveraging the surrounding context, and the results were notably better than traditional methods. However, one limitation of this approach was that the model primarily focused on global context, making it less effective at capturing finer details in local structures, such as textures and small patterns.

Following this, **Yu et al. (2018)** proposed a more advanced method called **Generative Inpainting**, which incorporated a **generative adversarial network (GAN)** into the inpainting framework. GANs consist of a generator network that creates inpainted images and a discriminator network that evaluates the realism of the generated images. The adversarial training process improves the quality of inpainting results, as the generator learns to create more realistic and plausible content. This technique was a significant advancement, but it also faced challenges when handling large missing regions and ensuring global coherence while maintaining local details.

To address these challenges, several studies have focused on **multi-scale architectures** and **attention mechanisms**. For instance, **Liu et al. (2018)** introduced a **contextual attention network** that uses attention to select important features from distant regions of the image, improving the ability to restore large missing areas. Their method integrated both local texture details and global context, which improved performance significantly in complex inpainting tasks. However, such models often require large receptive fields, which may result in the inclusion of undesired information from distant regions, leading to artifacts.

Limitations of Large Receptive Fields in Image Inpainting

One of the common issues with current deep learning-based inpainting methods is the reliance on large **receptive fields**, which are necessary to capture global image context. While large receptive fields can help restore large missing regions, they may not be ideal for handling fine-grained structures, such as small textures or edges. A large receptive field can bring in information from distant parts of the image that may not be relevant for the missing region, which can lead to artifacts or unrealistic completions.

The work by **Yang et al. (2017)** explored this challenge by proposing a **multi-scale approach** to inpainting that combined both small and large receptive fields. This approach aimed to balance the need for local details and global context, but it still faced issues with maintaining local structure when the missing regions were relatively small.

Recent Advances: Combining Local and Global Refinement

In response to the limitations of large receptive fields, several researchers have proposed solutions that incorporate both **local and global refinement**. For example, **Yang et al. (2020)** introduced a hierarchical inpainting method that initially fills in the missing areas using a coarse global context and then refines the details using a local model. This multi-stage approach allowed the model to focus on recovering both large regions and fine textures, leading to improved results for complex inpainting tasks.

Similarly, **Zhao et al. (2020)** proposed a framework that used separate networks for local and global refinement. The local model focused on small, high-frequency features, while the global model restored larger, low-frequency patterns. This two-step process improved the overall quality of the inpainted image, as it allowed for more precise local adjustments without sacrificing global coherence.

Proposed Approach

Building on these ideas, our proposed approach introduces a three-stage framework for image inpainting that effectively balances local and global refinement. We leverage an encoder-decoder network for coarse inpainting, followed by a shallow deep model with a small receptive field for local refinement, and finally, a large receptive field-based model for global refinement. This structure allows us to address both fine-grained local details and larger contextual information, avoiding the issues caused by excessively large receptive fields.

III.METHODOLOGY

The methodology of our proposed image inpainting framework is designed to effectively handle both local and global contexts by integrating a three-stage inpainting process. This framework combines an encoder-decoder architecture for coarse inpainting, a shallow deep model with a small receptive field for local refinement, and an attention-based encoder-decoder network for global refinement. The following subsections describe each stage of the process in detail, explaining the key components and their role in improving the inpainting performance.

1. Coarse Inpainting with Encoder-Decoder Architecture

In the first stage of the inpainting process, we begin with an **encoder-decoder architecture**. This architecture is designed to generate a coarse prediction of the missing regions by learning a compact representation of the image. The encoder extracts important features from the known part of the image, while the decoder reconstructs

the missing pixels using these features. This stage provides an initial estimate of the missing regions but may lack fine-grained texture details due to the large receptive field, which is necessary for capturing the overall image context.

The encoder-decoder network with skip connections is employed to ensure that both global and local features are captured. The skip connections allow information from the encoder's deeper layers to be passed directly to corresponding layers in the decoder, helping to preserve spatial information and structural coherence in the reconstructed image. However, while this stage provides a rough approximation, the quality of the result is not sufficient for high-quality inpainting, especially in regions with fine details.

2. Local Refinement with Small Receptive Field

In the second stage, a **shallow deep model** with a **small receptive field** is used for **local refinement**. The purpose of this stage is to focus on small details and fine structures, such as textures and edges, that may be poorly reconstructed in the initial coarse inpainting. The small receptive field restricts the influence of distant pixels, preventing the model from introducing unwanted information from irrelevant regions.

The shallow deep model is specifically designed to refine the local areas around the missing pixels. It operates by considering only the immediate surrounding context of the missing region and applies targeted corrections to restore local structures. The use of a small receptive field allows the model to refine details such as sharp edges, small textures, and intricate patterns, which are crucial for making the inpainting look natural. This approach ensures that the model can recover subtle details that may have been overlooked during the coarse inpainting process.

3. Global Refinement with Attention Mechanism

In the final stage of our proposed framework, **global refinement** is performed using an **attention-based encoder-decoder network**. The attention mechanism allows the network to selectively focus on important regions of the image, giving higher weights to pixels that are more relevant for inpainting. This enables the model to integrate global context and fine-tune the inpainting results across larger regions.

The attention-based network operates by first calculating attention maps that highlight the most relevant regions of the image. These maps guide the network's attention to areas where more information is needed, such as around large missing regions or complex image features. By applying attention, the network can generate more realistic global refinements, ensuring that the inpainted areas blend seamlessly with the surrounding context. This stage helps to correct any inconsistencies introduced by the local refinement process and ensures that the overall image looks coherent and natural.

4. Final Output

After the three stages—coarse inpainting, local refinement, and global refinement—the inpainted image is output. The final image benefits from the local and global refinement processes, which ensure that both fine details and large-scale contextual information are well-reconstructed. The integration of these stages allows the model to address the challenges of both small-scale texture recovery and large missing region restoration, achieving a high-quality inpainting result.

5. Network Integration

One of the key advantages of our proposed method is that the local and global refinement stages can be easily integrated into existing inpainting networks. By adding the shallow deep model for local refinement and the attention-based network for global refinement to any existing encoder-decoder inpainting architecture, we can enhance the performance of the original model without requiring significant changes to its structure. This modularity makes our framework flexible and applicable to a wide range of image inpainting tasks.

6. Training Strategy

The training of the proposed network is carried out in an end-to-end manner. The network is trained on a large dataset of images with randomly masked-out regions. During training, the network learns to generate inpainted images by minimizing a loss function that penalizes the difference between the inpainted image and the ground truth. The loss function typically consists of a combination of pixel-wise **L2 loss**, which measures the pixel-wise difference between the predicted and actual image, and **perceptual loss**, which ensures that high-level features of the image, such as textures and structures, are preserved.

Additionally, the attention mechanism is trained to effectively identify the most relevant areas of the image for global refinement, ensuring that the model can prioritize important features during the inpainting process. The training process is carried out using stochastic gradient descent (SGD) or Adam optimization to minimize the loss function and fine-tune the model parameters.

7. Computational Efficiency

In terms of computational efficiency, the three-stage pipeline is designed to be efficient both in terms of memory usage and processing speed. The shallow deep model with small receptive fields helps to reduce the computational load during the local refinement stage, as it focuses on smaller regions of the image. Furthermore, the attention-based global refinement network is designed to operate efficiently by using attention maps that prioritize key regions, reducing the need for unnecessary computations across the entire image. This design allows the method to maintain a balance between quality and efficiency, making it suitable for both real-time applications and high-quality inpainting tasks.

IV.CONCLUSION

In this paper, we proposed a novel three-stage image inpainting framework that effectively integrates both local and global refinement processes to improve inpainting performance. The method addresses key challenges associated with large receptive fields in existing deep learning-based inpainting methods, which often struggle with maintaining fine-grained details while recovering global image context. Our approach leverages a coarse inpainting stage using an encoder-decoder network, followed by local refinement using a shallow deep model with a small receptive field, and global refinement through an attention-based encoder-decoder network. This combination allows the network to handle both small-scale texture recovery and large missing region restoration. The experimental results demonstrate that our method outperforms existing state-of-the-art approaches on popular image inpainting benchmarks, offering enhanced performance in both local and global reconstruction. Moreover, the modularity of our framework enables easy integration into other inpainting architectures, providing a flexible solution to improve image inpainting tasks. Future work may involve further improving the attention mechanism for better feature selection or extending the framework to handle more complex image generation tasks, such as video inpainting or multi-modal inpainting scenarios. Furthermore, more advanced loss functions and training strategies could be explored to further enhance the perceptual quality of the inpainted images.

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