Multiresolution Hash Encoding as Image Prior

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1 Motivation

The process of image denoising is pivotal in enhancing the quality of digital images, finding its application across various domains such as medical imaging, satellite imagery, and photography. Despite its critical role, achieving high-quality denoising without compromising on detail remains a challenging task.

The quest for optimal image denoising methods has led to the exploration of numerous techniques[1, 2], with a significant focus on deep learning in recent years. Traditional methods often struggle to balance noise reduction with the preservation of image details, leading to either over-smoothed images or residual noise. This project is motivated by the need for advanced denoising techniques that can surpass these limitations, offering both high efficiency and quality.

2 Related Work

This project builds on the foundational work of the Deep Image Prior[3], which demonstrated that deep networks can inherently act as priors for image restoration tasks without requiring explicit training on noisy datasets. While groundbreaking, the Deep Image Prior has limitations in terms of computational efficiency and scalability. On the other hand, instant-ngp[4] from Nvidia provides a demonstration on gigapixel image tasks, showing its potential as image prior for denoising, but yet to be applied for use cases.

3 Project Overview

The core objective of this project is to apply the multiresolution hash table from instant-ngp as an image prior for denoising, and compare the results with the Deep Image Prior in terms of image denoising performance, specifically evaluating efficiency, speed, and Peak Signal-to-Noise Ratio (PSNR). This comparison aims to identify which method offers a superior balance of image quality improvement and computational demand, thereby setting a new standard for image denoising tasks. The project will also adjust the large amount of free hyperparameters of instant-ngp for this task.

The project will employ a structured experimental approach, starting with the collection and preparation of a diverse set of images subject to various noise levels. Both the gigapixel prior and the Deep Image Prior will be implemented and applied to these images. The evaluation will focus on quantitative metrics such as PSNR, as well as qualitative assessments of image quality, to comprehensively compare the performance of the two methods.

The project anticipates demonstrating the gigapixel prior's superiority or specific advantages over the Deep Image Prior in image denoising tasks. It aims to provide insights into how the computational efficiency, speed, and image quality improvements can be harnessed in practical applications, potentially revolutionizing the approach to image denoising.

4 Milestones and Timeline

1. Week 7: Complete a thorough literature review and finalize the project plan.
2. Week 8: Implement the gigapixel prior and integrate it with the denoising task.

3. Week 9: Conduct benchmark tests comparing the gigapixel prior with the Deep Image Prior, analyze results, identify areas for optimization, and refine methodologies.
4. Week 10: Final evaluation and preparation of the comparative analysis report.

References

[1] A. Buades, B. Coll, and J.-M. Morel. A non-local algorithm for image denoising. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 2, pages 60–65 vol. 2, 2005.

[2] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. *IEEE Transactions on Image Processing*, 16(8):2080–2095, 2007.

[3] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky. Deep image prior. *International Journal of Computer Vision*, 128(7):1867–1888, March 2020.

[4] Thomas Müller, Alex Evans, Christoph Schied, and Alexander Keller. Instant neural graphics primitives with a multiresolution hash encoding. *CoRR*, abs/2201.05989, 2022.