Digital Image Processing – 236860

Final Project

BP-DIP: A Backprojection based Deep Image Prior

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Introduction

Image deblurring is a common challenge in digital photography and computer vision, where the goal is to restore the original quality of an image that has been blurred.

Traditional methods often rely on large datasets for training and might not work well when the actual images they are applied to differ from the training images.

This paper examines a method called BP-DIP, which combines Deep Image Priors (DIP) with a Backprojection (BP) fidelity term. This approach uses the built-in features of convolutional neural networks (CNNs) to improve image restoration without needing pre-training on large datasets. Our study will look closely at how BP-DIP works, discuss its strengths and weaknesses, and suggest possible improvements.

Background and Related Works

Deep Image Priors (DIP) use the natural tendencies of CNNs to fix common image issues like noise, blurriness, or missing details. This method starts with a CNN that hasn't learned from any data yet and gradually improves the image directly from its degraded state. The Backprojection (BP) fidelity term, originally from medical imaging, has been adapted for use in cleaning up blurred images. It provides a solid alternative to traditional methods by making sure the restored image aligns well with the expected structure of the image before it was blurred.

Other researchers have expanded on the ideas of DIP and BP, trying out different ways to combine them with other techniques to make them even more effective and efficient. These studies have led to new approaches that balance the need for accuracy with the need to run computations quickly.

Theory and Methods

BP-DIP Overview: The BP-DIP method combines the concepts of Deep Image Prior (DIP) and Backprojection (BP) fidelity to enhance image restoration. It utilizes the unique structure of convolutional neural networks (CNNs) as a tool to progressively refine degraded images without relying on external training data.

Deep Image Prior (DIP):

- Definition: In DIP, a CNN is initialized randomly and used to iteratively refine a degraded image. The key formula used in DIP is:

$$x = f_{\theta}(z)$$

where is the estimated image, f_θ represents the CNN with parameters θ, and z is a fixed tensor filled with noise, providing the initial 'guess' for the image.

- Optimization Objective: The DIP works by minimizing the following loss function:

$$\min_{\theta} ||y - Af_\theta(z)||_2^2$$

where y is the degraded image and A is the degradation operator, such as a blur kernel.

Backprojection (BP) Fidelity Term:

- Definition: Traditionally used in computed tomography, BP helps to ensure that the reconstructed image adheres to the measured data. For image restoration, it is formulated as:

$$\mathrm{l}(x, y) = \frac{1}{2} ||A^{\dagger}(y - Ax)||_2^2$$

where $A^\dagger$ (the pseudoinverse of A) projects the difference between the observed degraded image y and the model output Ax back onto the input space.

- Integration in DIP: When combined with DIP, the loss function becomes:

$$\min_{\theta} ||A^{\dagger}\left(y - Af_\theta(z)\right)||_2^2$$

This modification helps in focusing the optimization on features more aligned with the underlying structure before degradation.

Fourier Domain Transformation:

- Transforming the BP Fidelity Term: To improve computational efficiency and address the convolution operations effectively, the problem is transformed into the Fourier domain:
$$\min_{\theta} ||F^* \left(\frac{1}{\sqrt{|F(h)|^2 + \epsilon_1 \sigma^2 + \epsilon_2}} \cdot F\big(y - h * f_{\theta}(z)\big) \right) ||_2^2$$
Here, F and F∗ denote the Fourier transform and its inverse, respectively. This transformation simplifies the convolution operations to multiplications, which are computationally more efficient to handle, especially using FFT algorithms.

Combining DIP and BP:

- Improved Objective: The integrated method aims to leverage the strengths of DIP's ability to model image statistics and BP's precision in adhering to the physical measurements. This is achieved by modifying the CNN's parameters to minimize a loss function that incorporates the BP term, leading to a potentially more accurate restoration:
$$\min_{\theta} ||A^{\dagger}\big(y - Af_{\theta}(z)\big)||_2^2$$
This combined approach uses the strengths of DIP's modeling capabilities and BP's adherence to physical measurements to achieve a more precise and effective image restoration.

- Example Application: In image deblurring, where A represents convolution with a blur kernel, the combined approach allows for more precise handling of the deblurring process, reducing artifacts and enhancing clarity.

Analyzation and testing of the algorithm

After testing the algorithm on some of the photos provided for us, we got the following results:

Original | Blurred | Restored using BP-TV

In the experiment, 3 types of kernels were used:

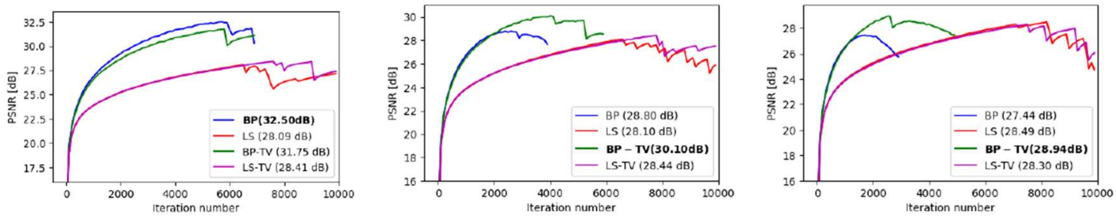
- Uniform kernel
- Radian kernel
- Gaussian kernel

And the following results were achieved:

TABLE I: Deblurring results (PSNR [dB] / SSIM averaged over Set14) of the different methods

	Uniform kernel			Radial kernel			Gaussian kernel		
	$\sigma=\sqrt{0.3}$	$\sigma=\sqrt{2}$	$\sigma=\sqrt{4}$	$\sigma=\sqrt{0.3}$	$\sigma=\sqrt{2}$	$\sigma=\sqrt{4}$	$\sigma=\sqrt{0.3}$	$\sigma=\sqrt{2}$	$\sigma=\sqrt{4}$
LS	26.31 / 0.83	26.84 / 0.84	26.45 / 0.83	28.09 / 0.88	28.10 / 0.88	28.49 / 0.87	27.42 / 0.87	27.22 / 0.86	27.66 / 0.86
LS-TV	26.36 / 0.83	26.95 / 0.84	26.80 / 0.84	28.41 / 0.88	28.44 / 0.88	28.30 / 0.88	27.74 / 0.86	27.31 / 0.85	27.62 / 0.86
BP	**29.78 / 0.91**	26.57 / 0.84	25.41 / 0.80	**32.50 / 0.95**	28.80 / 0.89	27.44 / 0.86	**29.73 / 0.91**	27.13 / 0.85	26.05 / 0.82
BP-TV	29.51 / 0.90	**28.25 / 0.88**	**27.31 / 0.86**	31.75 / 0.93	**30.10 / 0.91**	**28.94 / 0.89**	29.65 / 0.91	**28.94 / 0.90**	**28.24 / 0.88**

(a) Uniform kernel, $\sigma=\sqrt{0.3}$ (b) Uniform kernel, $\sigma=\sqrt{2}$ (c) Uniform kernel, $\sigma=\sqrt{4}$



And as we can see, different PSNR values were achieved for the different kernels used.

Discussion of Limitations

Noise Sensitivity:

- Issue: The BP-DIP method, while robust in handling various types of degradation, is particularly sensitive to high noise levels. This sensitivity can lead to suboptimal restoration outcomes where noise is mistakenly interpreted as part of the image structure.
- Impact: Excessive noise can lead to overfitting during the restoration process, where the model may enhance noise instead of filtering it out.

Computational Demand:

- Issue: Despite the efficiency improvements offered by the Fourier transform, the BP-DIP method remains computationally intensive, especially when dealing with high-resolution images or when extended to three-dimensional data.
- Impact: The high computational cost can limit the practical application of BP-DIP in real-time processing environments or on devices with limited processing capabilities.

Generalization Across Different Types of Image Corruptions:

- Issue: The current implementation of BP-DIP is primarily optimized for deblurring tasks. Its effectiveness for other types of image corruption, such as severe occlusions, heavy noise in low-light images, or artifacts introduced by different types of motion, has not been thoroughly tested.
- Impact: This limitation may restrict the utility of BP-DIP to a narrower range of applications, reducing its versatility compared to more generalized image restoration methods.

Proposed Enhancements

Enhanced Noise Handling:

- Solution: Integrate adaptive noise filters or more sophisticated regularization techniques within the BP-DIP framework to better differentiate between noise and actual image content.
- Expected Benefit: Improved restoration quality with reduced noise artifacts, enhancing the method's robustness across various noise levels.

Optimization and Efficiency Improvements:

- Solution: Explore alternative optimization algorithms that could accelerate convergence or reduce computational overhead. Implementing more efficient ways to handle large-scale data, such as using GPU acceleration or distributed computing frameworks, could also be beneficial.
- Expected Benefit: Faster processing times and reduced computational demands, making BP-DIP feasible for real-time applications and on devices with limited hardware capabilities.

Broadening the Application Scope:

- Solution: Conduct experimental validations of BP-DIP across a wider range of degradation types and integrate modular components that can be tailored to specific types of image corruption.
- Expected Benefit: A more flexible and adaptable BP-DIP method capable of handling a broader array of image restoration tasks, enhancing its applicability in diverse real-world scenarios

Additional Exploration

Application to Other Forms of Image Degradation:

- Overview: While BP-DIP has been primarily applied to deblurring, its potential extends to other forms of image degradation such as denoising, super-resolution, and inpainting.
- Proposed Experiment: Test the BP-DIP framework on a dataset affected by severe noise and low resolution to evaluate its effectiveness in noise reduction and resolution enhancement. Utilize both synthetic and real-world images to assess performance comprehensively.

Integration with Machine Learning Techniques:

- Overview: Integrating BP-DIP with advanced machine learning techniques such as Generative Adversarial Networks (GANs) or reinforcement learning could potentially open new avenues for adaptive image restoration.
- Proposed Experiment: Develop a hybrid model that uses a GAN where the BP-DIP serves as the generator, and a discriminator assesses the quality of the restored images. This setup could refine the restoration process by learning optimal filters and restoration strategies adaptively.

Real-Time Processing for Video Restoration:

- Overview: Extending BP-DIP to video restoration involves addressing the additional challenge of temporal consistency along with spatial image quality.
- Proposed Experiment: Implement BP-DIP in a video processing pipeline to handle motion blur and frame-by-frame degradation. Test the efficacy of the method on video data from various sources, including CCTV footage and drone videos, focusing on reducing artifacts and enhancing clarity.

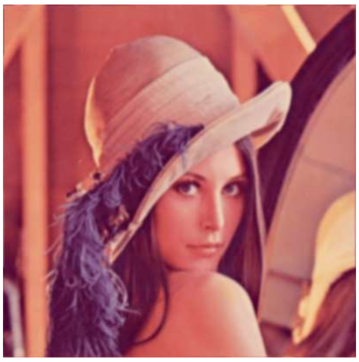
Adaptation for Medical Imaging:

- Overview: Medical imaging, such as MRI or CT scans, often requires precise image restoration techniques to improve the clarity and utility of the images for diagnostic purposes.
- Proposed Experiment: Adapt the BP-DIP method to the specific requirements of medical imaging, focusing on enhancing images while preserving critical diagnostic details. Collaborate with medical professionals to tailor the approach and validate its effectiveness on clinical data sets

Testing Different Loss Functions:

In our study, we tried out different ways to measure how well our image restoration worked by using various loss functions. These included Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Structural Similarity Index (SSIM). Each of these measurements looks at image quality from different angles. PSNR checks for the maximum possible error, MSE and MAE calculate the average differences, and SSIM measures changes in patterns and brightness in the images. By using these different metrics, we hoped to get a clear picture of how well our method was improving the distorted images. Here are some of the results:

Original

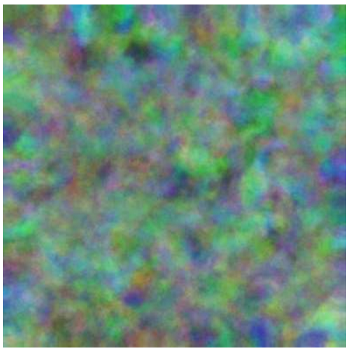


Blurred

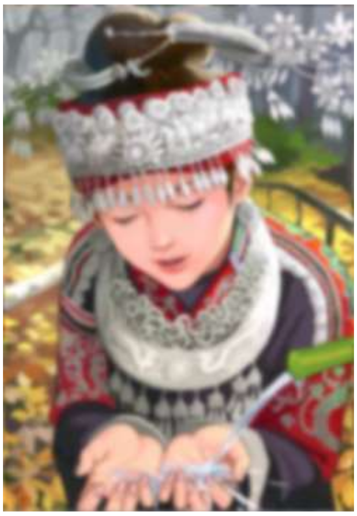
Reconstructed using PSNR

Reconstructed using MSE

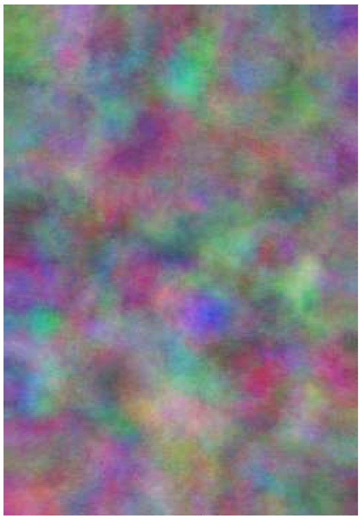
Reconstructed using MAE



Reconstructed using SSIM



Original **Blurred** **Reconstructed using PSNR**



Reconstructed using MSE **Reconstructed using MAE** **Reconstructed using SSIM**

Out of the different loss function we tried, the PSNR seems to give the best results.

Issue with SSIM Results:

When we looked at the results, we found that the numbers we got from using SSIM didn't make sense. They were very off compared to what we expected. We checked everything from how we set up our experiments to how we were calculating the results, but we couldn't figure out why SSIM was giving us such strange results.

Using a Different Denoising Technique:

Instead of using the bm3d_deblurring method that the original paper used, we decided to try something else called denoise_tv_chambolle. This method is good at removing noise from images while keeping their sharp edges by focusing on reducing the overall change in color and brightness across the image. We chose this technique because it's supposed to be really good at cleaning up images without blurring out important details. By trying a different approach, we wanted to see if we could get even better results or learn something new about improving our image restoration method.

Summary:

The article "BP-DIP: A Backprojection based Deep Image Prior" introduces a way to improve image quality using deep learning, without needing a lot of pre-existing data. This is especially useful because traditional methods can struggle when there's a mismatch between how they were trained and how they're used in real situations. The approach combines two techniques—Deep Image Prior and Backprojection fidelity—to adapt better to different testing conditions.

Reading this article and experimenting with its concepts was both enjoyable and educational. The writing was clear and the structure made it easy to understand the complex ideas involved. The subject of using deep learning to fix image problems is really interesting and feels relevant to today's tech challenges. Working through the paper, especially testing different loss functions like PSNR, MSE, MAE, and SSIM, made the theoretical part much more tangible.

This study is not just academically sound but also very practical, offering better ways to handle image restoration when typical large datasets aren't available. It was great to see how these new ideas could change real-world applications, making the whole experience of reading and applying the concepts from the paper quite rewarding.