F74094083 林欣誠 GAI HW4

Github Link:

https://github.com/Dkoctro/GAI_F74094083_HW4

- ## Theoretical Justification

(1) The proposed solution aims to enhance the efficiency and quality of image generation by combining DDPM with DIP. DDPM is good at generating high-quality images by modeling complex data distributions through a sequence of denoising steps, but it is computationally intensive. On the other hand, DIP leverages the inherent regularization properties of CNNs to generate high-quality images from noise without requiring a large dataset. By using DIP to generate an initial image, we provide a good starting point for allows DDPM to refine an already reasonable approximation, thereby speeding up the overall process while maintaining high image quality.

(2) The primary design choice of accelerating DDPM with DIP-based Initial Priors is leveraging the strengths of DIP

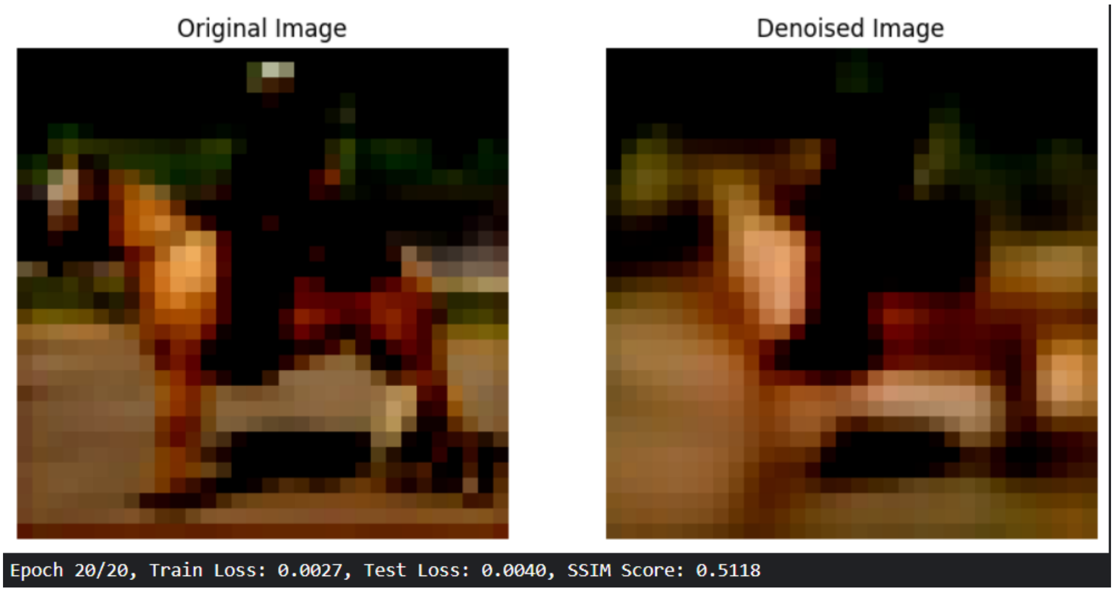
to create an initial guess, which then serves as a prior for DDPM refinement. The rationale behind this choice is that DIP can quickly generate a high-quality initial image using CNNs' regularization properties, significantly reducing the complexity and computational load for the subsequent DDPM steps. The key assumption here is that the image generated by DIP is close enough to the targe image that DDPM can effectively fine-tune it with fewer denoising steps. This assumption is critical because the efficiency gain depends on the quality of the initial guess. If the initial image is within a reasonable range of the target distribution, DDPM can perform fewer and more effective refinement steps, accelerating the entire process.

(3) Combining DDPM with DIP-based initial priors offers several benefits. Firstly, it increases efficiency by reducing the number of DDPM steps needed, which lowers computational costs and speeds up inference times. Secondly, it maintains the high-quality output

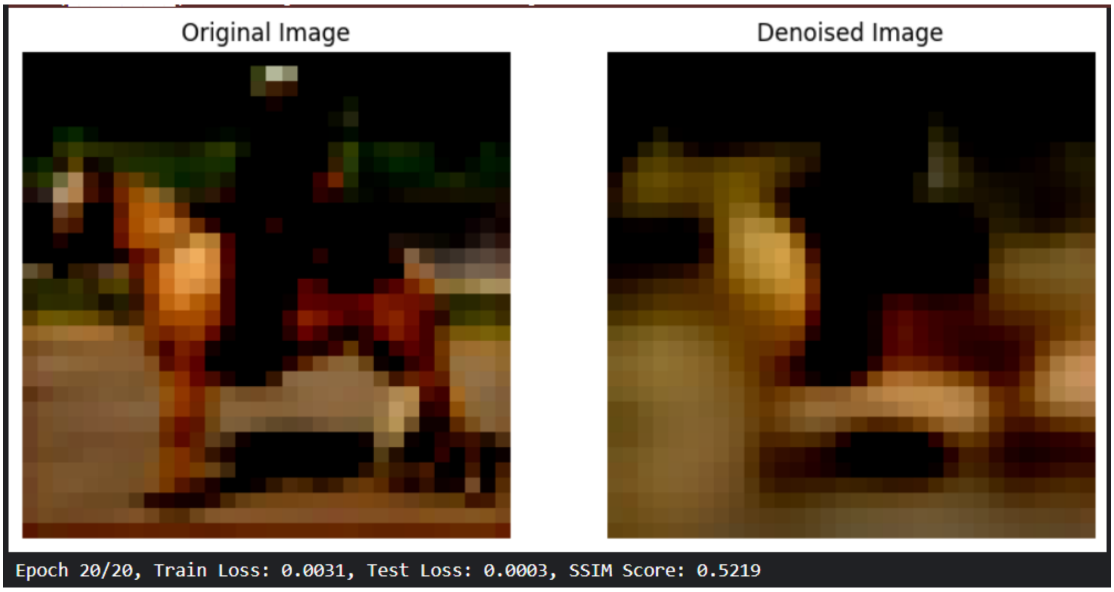
characteristic of DDPM while leveraging the quick initial approximation provided by DIP. Lastly, this approach is versatile and can be applied to various image restoration tasks, potentially improving both speed and quality across different applications. However, there are limitations. The quality of the final image heavily relies on the initial prior generated by DIP. If the initial guess is not sufficiently close to the target, the combined approach's benefits might be diminished. Additionally, integrating two sophisticated models introduces complexity in implementation, training, and fine-tuning, requiring careful balancing and potentially making the approach more challenging to execute compared to using DDPM or DIP alone.

- **Experimental Verification**

  Only DDPM:



Accelerating DDPM with DIP-based Initial Priors:



After 20 epochs, the ssim score is 0.5219

With DIP-based, the score of ssim has improved.

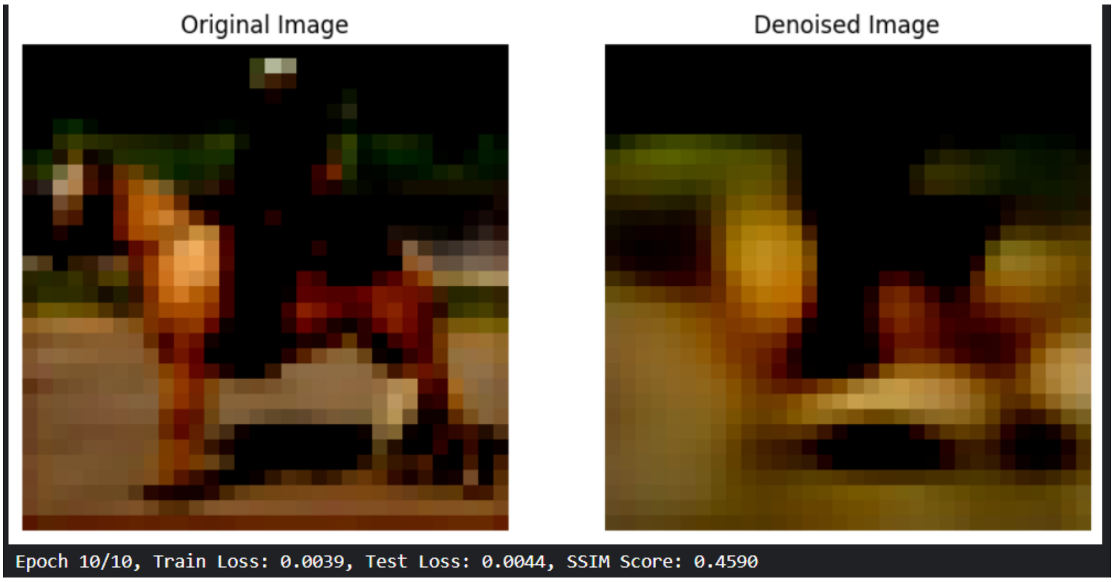
I think the reason why ssim score improve is that DIP

provides a strong initial guess for the denoised image.

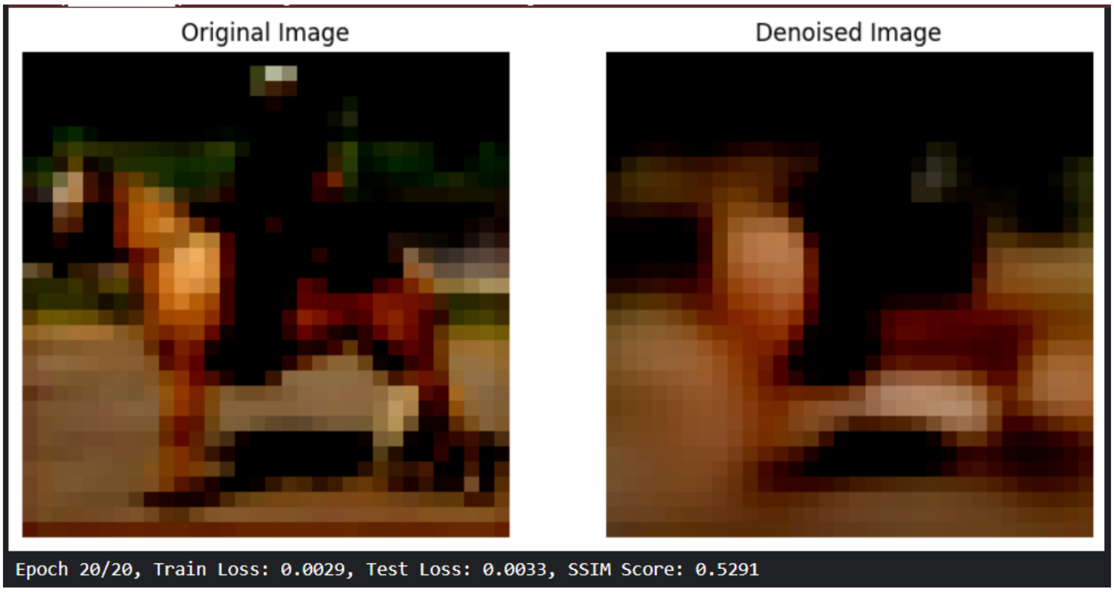
This initial guess can be closer to the true image, reducing the burden on the DDPM model to recover fine details from the noisy image.

- **Ablation Studies and Analysis**

Only DDPM:

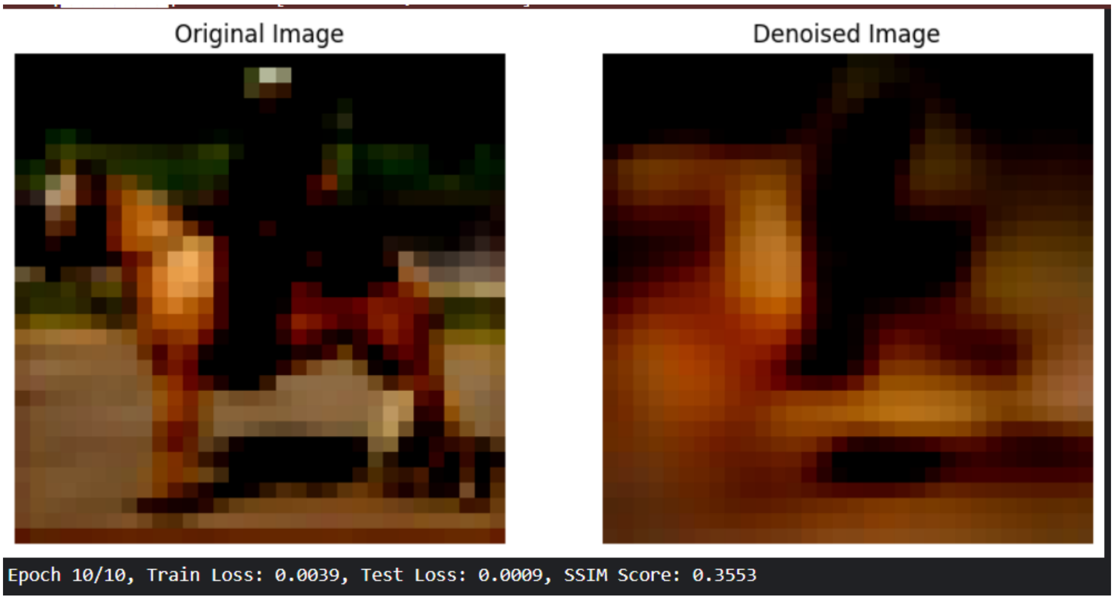


SSIM Score: epoch number = 10 < number = 20



SSIM Score: learning rate = 0.0001 > learning rate = 0.001

Accelerating DDPM with DIP-based Initial Priors:



SSIM Score: epoch number = 10 < number = 20

SSIM Score: learning rate = 0.0001 > learning rate = 0.001