CSC2529 Computational Imaging Project

Guiding Deep Image Prior with Traditional Image Recovery Methods

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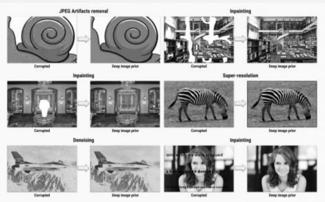
MOTIVATION

- In machine learning and neural networks, most solutions require the trained models to approximate the original image using **patterns observed from other images** in the entire image set. Deep Image Prior (DIP) is an outlier: it recovers images **without training data**.
- In this project, we intend to leverage both DIP and traditional rule-based methods to form a new image recovery pipeline. We observe, compare, and analyze their performance.
- The **early stopping point** is a key concept in DIP. We are curious about what factors may affect it.

RELATED WORK

- Ulyanov et al. (2018) [1] proposed a powerful and effective method for imaging processing called **Deep Image Prior (DIP)**. Our project will be mainly based on evaluating and extending the DIP algorithm by using different image preprocessing methods.



- Several methods were investigated to **stop DIP iterations before fitting to noise** and thus prevent from overfitting, most of which requires the clean image as an input. However, in real world examples, clean images can be hard to retrieve, and it slightly contradicts the non-training objective of DIP.
- At the same time, many **extensions** can be made based on the idea of DIP. Bredell et al. came up with an idea that uses Wiener deconvolution to guide DIP for better performance on image deblurring. We may want to extend this idea and use different methods of denoising and deblurring to compare the results.

PROPOSED METHOD & EXPERIMENTAL RESULTS

In our project, we plan to investigate the mechanism and effectiveness of DIP, as well as potential improvements.

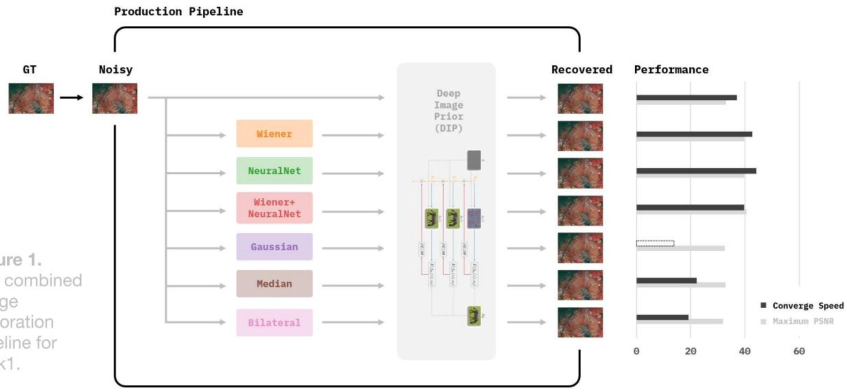


Figure 1. The combined image restoration pipeline for Task1.

- **Task 1.** If we manually denoise/deblur the image before training it with deep neural networks, will the result be better? To obtain the answer, we plan to utilize different image denoising/deblurring methods as preprocessing for the corrupted input image to the DIP and compare the final results.
- **Task2.** In the experimental setup, we plan to gather a variety of images and add the same noise to them, and observe the PSNR curve for possible patterns.

Our results show that when preprocessed with Wiener deconvolution or denoising neural networks, the performance is higher in terms of both maximum PSNR and converge speed compared to standalone DIP.

Also, the converge speed does not correlate significantly with noise levels, but rather the image content frequency.

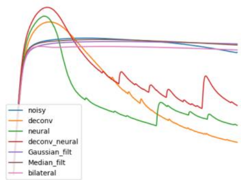
Figure 2. Optimal intermediate results at selected stop points.

(a)

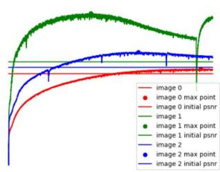
Methods	$\sigma = 0.01$			$\sigma = 0.02$			$\sigma = 0.05$		
	Initial PSNR	Optimal Stopping Point	Maximum PSNR	Initial PSNR	Optimal Stopping Point	Maximum PSNR	Initial PSNR	Optimal Stopping Point	Maximum PSNR
Standalone	32.12	2155	32.92	30.40	2701	32.88	25.23	1892	32.75
Wiener	28.93	4442	39.71	23.14	2341	38.47	15.33	964	34.76
NeuralNet	37.39	N/R	39.64	28.06	2262	38.26	19.11	823	35.47
Wiener+ NeuralNet	37.79	N/R	40.65	30.32	2514	39.73	21.14	907	36.56
Gaussian	32.55	N/R	32.57	32.36	N/R	32.53	31.25	2628	32.33
Median	32.74	N/R	32.87	32.32	4495	32.81	30.26	2322	32.58
Bilateral	31.91	N/R	31.97	31.64	5189	31.92	30.04	716	31.73

(b)

Methods	Image 0			Image 1			Image 2		
	Initial PSNR	Optimal Stopping Point	Maximum PSNR	Initial PSNR	Optimal Stopping Point	Maximum PSNR	Initial PSNR	Optimal Stopping Point	Maximum PSNR
Wiener	23.00	3854	30.58	23.14	2613	28.06	23.02	4857	29.81
NeuralNet	25.69	2341	38.47	28.06	2262	38.26	27.07	2514	39.73
Wiener+ NeuralNet	28.25	3439	33.31	30.32	2753	31.63	29.36	3666	33.23



(c)



(d)

Figure and Table 3. (a) Performance of standalone DIP and combined pipelines under different sigma values and a fixed image 1. (b) Performance of selected methods for different images and a fixed sigma value 0.02. (c) PSNR curve in training process for Image 1 for different methods. (d) PSNR curve for a fixed noise level and different images when using the Wiener+NeuralNet method.

REFERENCES

- Ulyanov et al. **"Deep image prior."** Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.
- Bredell, Gustav, et al. **"Wiener Guided DIP for Unsupervised Blind Image Deconvolution."** arXiv preprint arXiv:2112.10271 (2021).
- Jo et al. **"Rethinking deep image prior for denoising."** Proceedings of the IEEE/CVF Intl. Conference on Computer Vision. 2021.