EE5175 Lab 11

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Introduction

In this experiment, we will perform non-blind deblurring (NBD) using L_1 and L_2 norm based gradient regularization schemes. A proper description of the problem statement can be found in the assignment PDF.

L_2 Regularized NBD: PSNR vs Visual Comparison

We pick the best λ based on the minimum RMS between the clean and deblurred image and compare those results to the ones chosen for the best looking images. We also show the RMS plots for different values of λ. The image degradation parameters are

- $\sigma_n = 8$, a) $\sigma_b = 0.5$, b) $\sigma_b = 1$, c) $\sigma_b = 1.5$
- $\sigma_b = 1$, a) $\sigma_n = 5$, b) $\sigma_n = 10$, c) $\sigma_n = 15$,

The results are shown in Figure 1 to Figure 12.

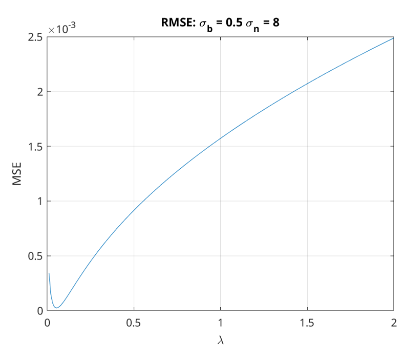


Figure 1: RMS: $\sigma_b = 0.5 \quad \sigma_n = 8$

L_2 vs L_1 Regularization

We perform NBD using L_2 gradient regularization and compare the results with that of L_1 gradient regularization. To obtain the result for L_1 gradient

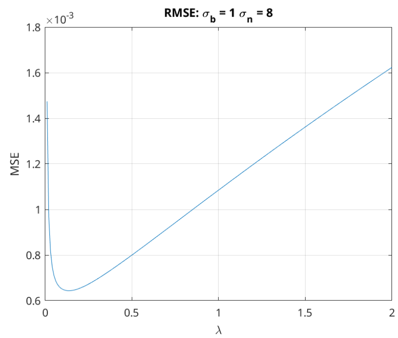


Figure 2: RMS: $\sigma_b = 1 \quad \sigma_n = 8$

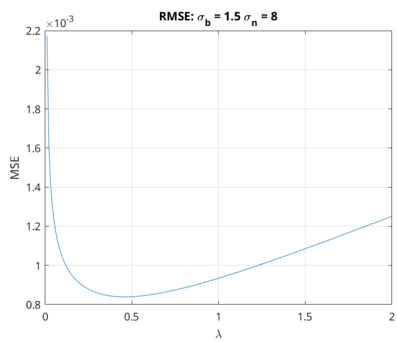


Figure 3: RMS: $\sigma_b = 1.5 \quad \sigma_n = 8$

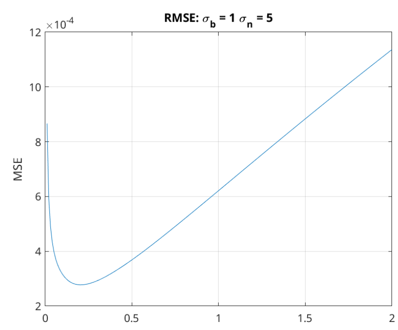


Figure 4: RMS: $\sigma_b = 1 \quad \sigma_n = 5$

regularization, we need to use the code 'admmfft.m' which uses the ADMM method to solve the optimization problem. We show the most visually appealing outputs by varying λ for the following scenarios.

- $\sigma_n = 1$, $\sigma_b = 1.5$

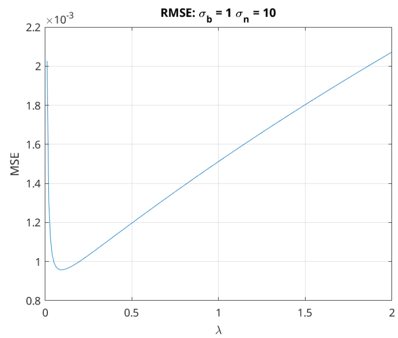


Figure 5: RMS: $\sigma_b = 1 \quad \sigma_n = 10$

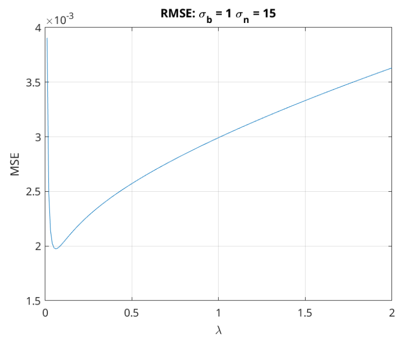
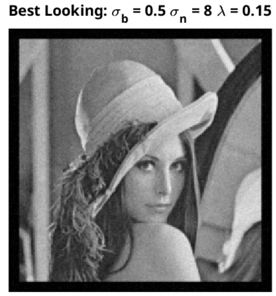


Figure 6: RMS: $\sigma_b = 1 \quad \sigma_n = 15$

(a) Lowest RMS



(b) Best Looking

Figure 7: $\sigma_b = 0.5 \quad \sigma_n = 8$

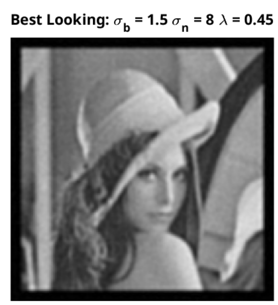
- $\sigma_n = 5$, $\sigma_b = 1.5$
- $\sigma_n = 5$, h=`mb-kernel.png` (motion blur)

(a) Lowest RMS

(b) Best Looking

Figure 8: $\sigma_b = 1 \quad \sigma_n = 8$

(a) Lowest RMS



(b) Best Looking

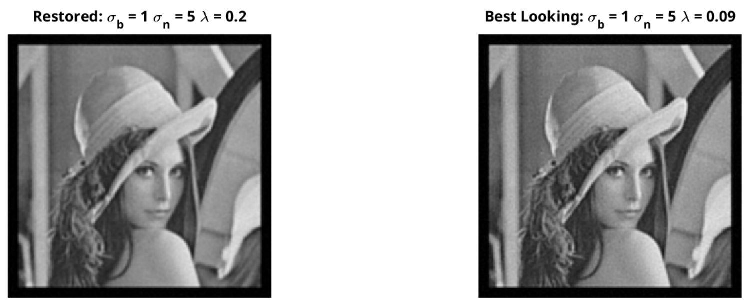
Figure 9: $\sigma_b = 1.5 \quad \sigma_n = 8$

The results are shown in Figure 13 to Figure 15.

Observations

The following observations can be made.

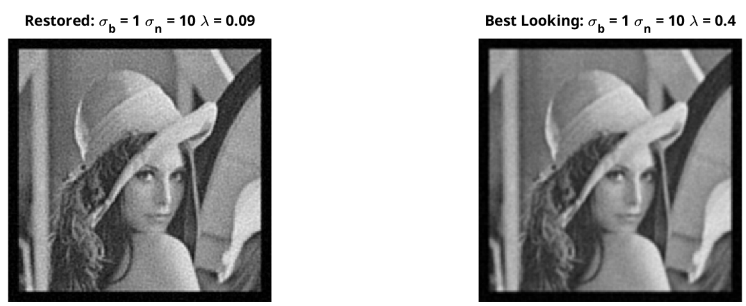
- Increasing λ leads to better noise reduction at the cost of a blurry image. Decreasing λ prioritizes sharpness over noise-reduction.
- While performing NBD with L_2 regularization, the λ that minimizes the MSE between the original image and the deblurred image increases with increasing σ_b when σ_n is held constant. We can infer it being an indicator of the fact that as the image degradation due to blurring gets more extreme, it is better to rely more on the priors than on the data.



(a) Lowest RMS

(b) Best Looking

Figure 10: $\sigma_b = 1 \quad \sigma_n = 5$

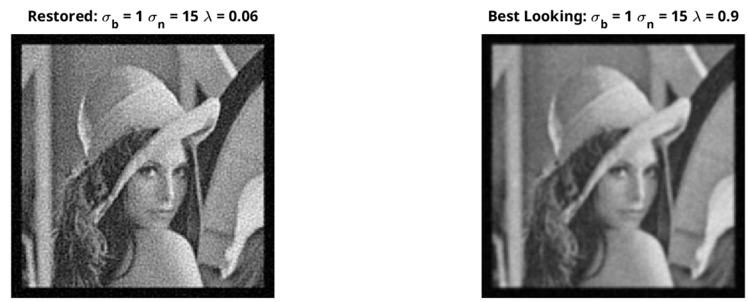


(a) Lowest RMS

(b) Best Looking

Figure 11: $\sigma_b = 1 \quad \sigma_n = 10$

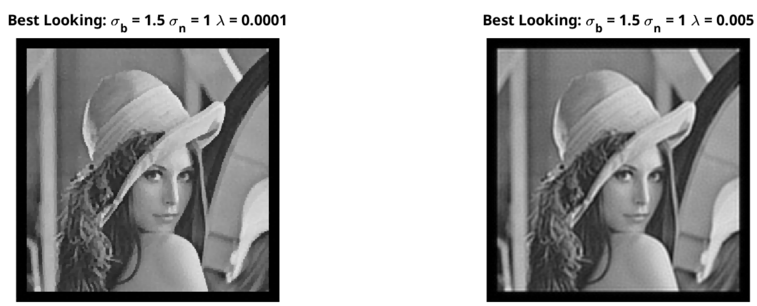
- While performing NBD with L_2 regularization, the λ that minimizes the MSE between the original image and the deblurred image decreases with increasing σ_n when σ_b is held constant. It is harder to draw inferences in this case compared to the previous one as the optimal λ decreasing might be due to the fact that a slightly noisy but sharp image probably has a lower MSE with the clean image compared to a non-noisy but blurred image.
- For the most visually pleasing image, the optimal λ increases with increasing σ_b when σ_n is held constant. This follows the same trend as the optimal λ to minimize the MSE between the degraded and clean image.
- For the most visually pleasing image, the optimal λ decreases with increasing σ_n when σ_b is held constant. This is opposite to the trend followed



(a) Lowest RMS

(b) Best Looking

Figure 12: $\sigma_b = 1 \quad \sigma_n = 15$



(a) L_1

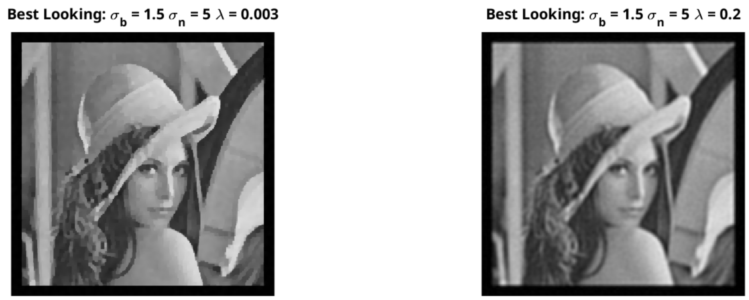
(b) L_2

Figure 13: $\sigma_b = 1.5 \quad \sigma_n = 1$

by the optimal λ to minimize the MSE between the degraded and clean image. This is probably due to the fact that a slightly blurry but clean image is more pleasing to look at than a sharp but noisy image.

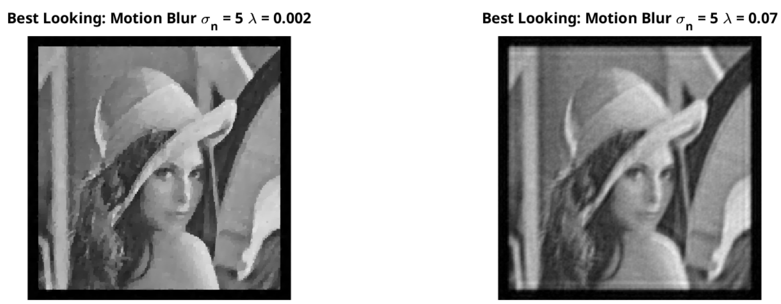
- Deblurring with L_1 regularization requires much smaller values of λ compared to deblurring with L_2 regularization. However, a small change in the value of λ causes a lot more change in the case of L_1 regularization compared to L_2 regularization.

- For the same amount of degradation, we can in general get a sharper looking image using L_1 regularization compared to L_2 regularization. The former preserves edges better than the latter, which has a tendency to smooth out edges and fine details.



(a) L_1 (b) L_2

Figure 14: $\sigma_b = 1.5 \quad \sigma_n = 5$



(a) L_1 (b) L_2

Figure 15: Motion Blur $\sigma_n = 5$

- Given that the L_2 regularized deblurring can be efficiently implemented in the frequency domain, it is much faster than L_1 regularized deblurring. There is hence a trade-off between performance and efficiency.
- For the motion blur case, deblurring with L_1 regularization completely removes motion blur artefacts, which are prominently visible in the L_2 regularization deblurring case. The former result is much more visually appealing.