

048000 – Computational Photography

Spring 2022

Wet Exercise 1

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Submission Date : 11/04/2022

Question 1

Calculation of σ^2

The calculation of σ^2 was done as proposed in the assignment. We defined two derivative kernels in x, y axes: g_x, g_y .

We calculated the clean image derivative with the supplied `conv_fft2` function: $X_{g_x} = X * g_x, X_{g_y} = X * g_y$. We summed the square values of the derivatives and applied a mean function to it: $\sigma^2 = \text{obsvar} = \text{mean}(X_{g_x}^2 + X_{g_y}^2)$.

The resulted value was $\sigma^2 = 0.0210$.

Calculation of η^2

It is given that $y = Ax + N$, where

y – *blurred image*,

A – *multiplication matrix representation of blur kernel*

x – *clean image*

N – *noise*

Therefore: $N = y - Ax$ and so we can estimate η^2 as follows:

$$\eta^2 = \text{Var}(N) = \text{Var}(y - Ax)$$

We used matlab's internal `Var` function, and derived η^2 as follows:

$$\eta^2 = 10^{-4} \times \begin{cases} 1.0025 & A = k_1 \\ 0.9923 & A = k_2 \\ 1.007 & A = k_3 \end{cases}$$

Note: η^2 is relatively close in all three estimations, and we could use the mean of them for all optimizations and get similar results, however we used each calculated η^2 w.r.t to its image.



Question 2

We got the following results:



Question 3

We got the following images:



Analysis:

Row 1: Deblurred images are relatively sharp with all three kernels, however with kernels 2 and 3 with start to see some artifacts which are prominent in letter edges. This is probably since image 1 was deblurred with kernel 1, and with the other 2 we do not satisfy the restrictions of $y = k * x + n$ as well.

Row 2: The image deblurred with kernel 1 is relatively sharp (less than images in row 1), and with kernel 3 we can still observe some artifacts. As expected, the best result was received with kernel 2, which was the blur kernel of image 2.

Row 3: Images 1 & 2 are relatively blurry, and image 3 seems to be the sharpest of the three (although blurrier than row 2).

We can assume that k_3 blurs the image more aggressively than k_1, k_2 , and k_2 more aggressively than k_1 , which is why the deblurring process works better in the first row, followed by the second, and lastly the third.

Question 4



Analysis:

Looking at the first column where $\eta = 10\eta^*$, we penalize the data term of the L2 distance term less: $\frac{1}{2\eta^2} \|y - Ax\|^2$, therefore we would expect that the optimization would prefer to minimize the Gaussian prior more, therefore resulting in a smoother image, and with less information from the blurred image itself.

The middle column matches the same optimization we've done in Q2 with a fair trade-off between the data and regularization term, and as expected we do get the best results out of the three columns.

The third column penalizes the data term much more than the regularization; therefore, we would expect an image which optimizes the L2 distance from the data, and less the smoothness. This results in unnatural patterns as if the prior barely affected the image.