Assignment 5: Discrete Fourier Transform

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Q5: Image Denoising using PCA

1. Part A

Original Image



Noisy Image



Denoised Image



Original Image



Noisy Image



Denoised Image



Fig 1: Global PCA Denoising of zero mean white Gaussian noise

For Barbara

RMSE of Noisy image: 0.023303 RMSE of Denoised image: 0.014963

For Stream

RMSE of Noisy image: 0.022

RMSE of Denoised image: 0.014743

2. Part B

Original Image



Noisy Image



Denoised Image



Original Image



Noisy Image



Denoised Image



Fig 2: Local PCA Denoising of zero mean white Gaussian noise

For Barbara

RMSE of Noisy image: 0.023027 RMSE of Denoised image: 0.011299

For Stream

RMSE of Noisy image: 0.020618 RMSE of Denoised image: 0.014391

3. Part C

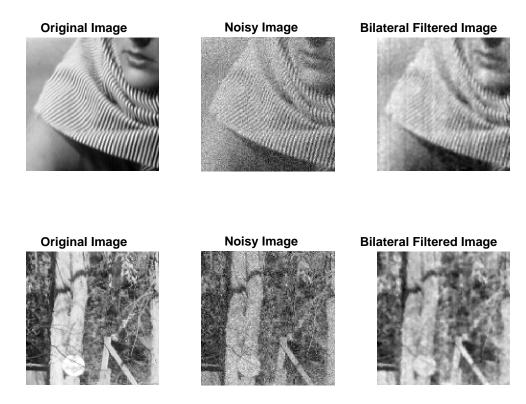


Fig 3: Bilateral Filtering

Comparison between PCA based approach results with that of the bilateral filter:

- There is significantly higher degree of staircasing artifacts in the bilateral filter output. In addition, there is a lot more undesired smoothing of textures in case of bilateral filtering. PCA approach does a better job at denoising.
- In general, bilateral filter has the limitations that texture softer than the intensity-kernel standard deviation are removed and staircase artifacts are introduced.
- Bilateral filter relies on the assumption that original image is piecewise constant in intensity.
- PCA based approach makes no such assumption as above. It assumes that given a small enough patch, there exist other patches in the image that are similar to it in structure. It uses the Wiener filter update that attenuates eigencoefficients corresponding to noise and leaves the original image textures unharmed.

4. Part D

a. Original Image (poissrnd(im))



a. Noisy Image (poissrnd(im))



a. Denoised Image (poissrnd(im))



b. Original Image (poissrnd(im/20))



b. Noisy Image (poissrnd(im/20))



b. Denoised Image (poissrnd(im/20))



Fig 4: Local PCA Denoising of Poisson noise (barbara)

For Barbara

• Part a. RMSE of Noisy image: 0.0071945

• Part a. RMSE of Denoised image: 8.7259e-05

• Part b. RMSE of Noisy image: 0.007673

• Part b. RMSE of Denoised image: 0.0074276

a. Original Image (poissrnd(im))



a. Noisy Image (poissrnd(im))



a. Denoised Image (poissrnd(im))



b. Original Image (poissrnd(im/20))



b. Noisy Image (poissrnd(im/20))



b. Denoised Image (poissrnd(im/20))

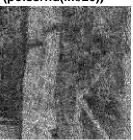


Fig 5: Local PCA Denoising of Poisson noise (stream)

For Stream

Part a. RMSE of Noisy image: 0.0072184

Part a. RMSE of Denoised image: 9.2493e-05

Part b. RMSE of Noisy image: 0.0076785

Part b. RMSE of Denoised image: 0.0074278

Comparison between poissrnd(im) and poissrnd(im/20):

- The latter [with poissonrnd(im/20)] actually represents image acquisition with a lower acquisition time and hence lower brightness.
- We observe that denoising is highly unsuccessful in the latter case (corroborated by RMSE values).
- One possible justification could be that as lower intensity brightness is captured, the magnitude of Poisson noise becomes more and more comparable.
- In addition, the Anscombe model is more accurate as I(signal variable) tends to infinity. Here we have drastically downscaled the pixel intensities leading to errors in the modelling assumption.

5. Part E

Effect of clamping the values in the noisy image 'im1' to the [0,255] range,:

- On denoising the noisy clamped stream.png image, an RMSE of 0.0105 is obtained compared to the earlier RMSE of 0.014588.
- This shows that the denoising after clamping noisy image values within the range of 0-255 helps in achieving a better denoising using PCA and can be considered as a correct approach.
- This could be explained by the fact that clamping the values forces the algorithm to stay within the original range of 0-255 & hence tends to decrease the variance of the noise, leading to better denoising.