

# Assignment 5: Discrete Fourier Transform

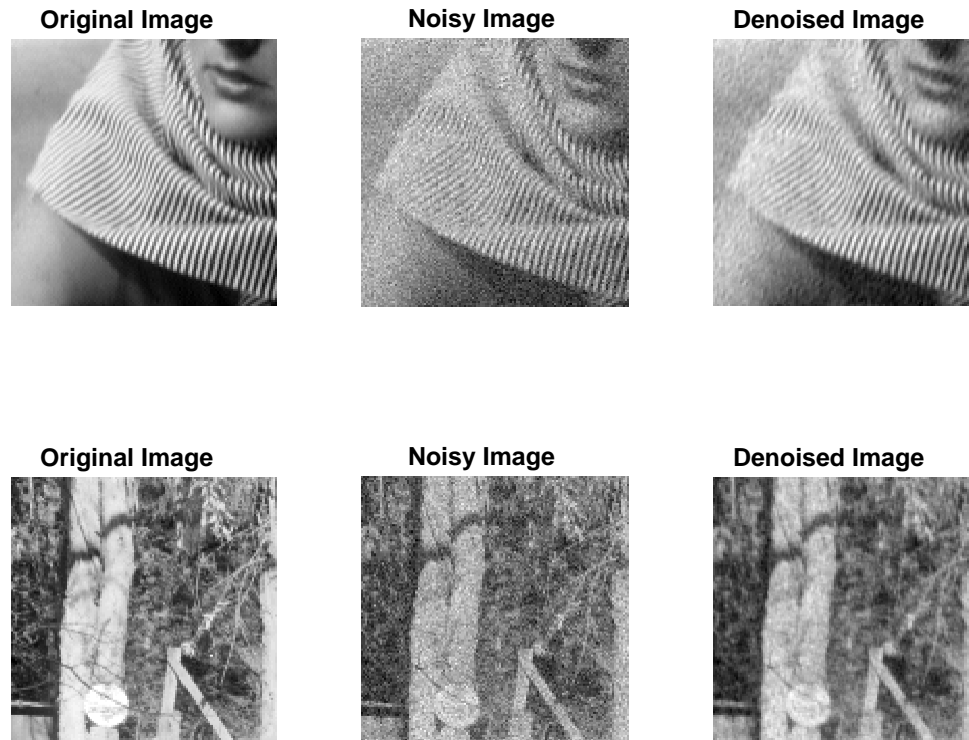
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*Due Date: 03/11/2019*

**Q4: Image Denoising using PCA**

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## 1. Part A



Pixel info: (92, 23) 182

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

For Barbara

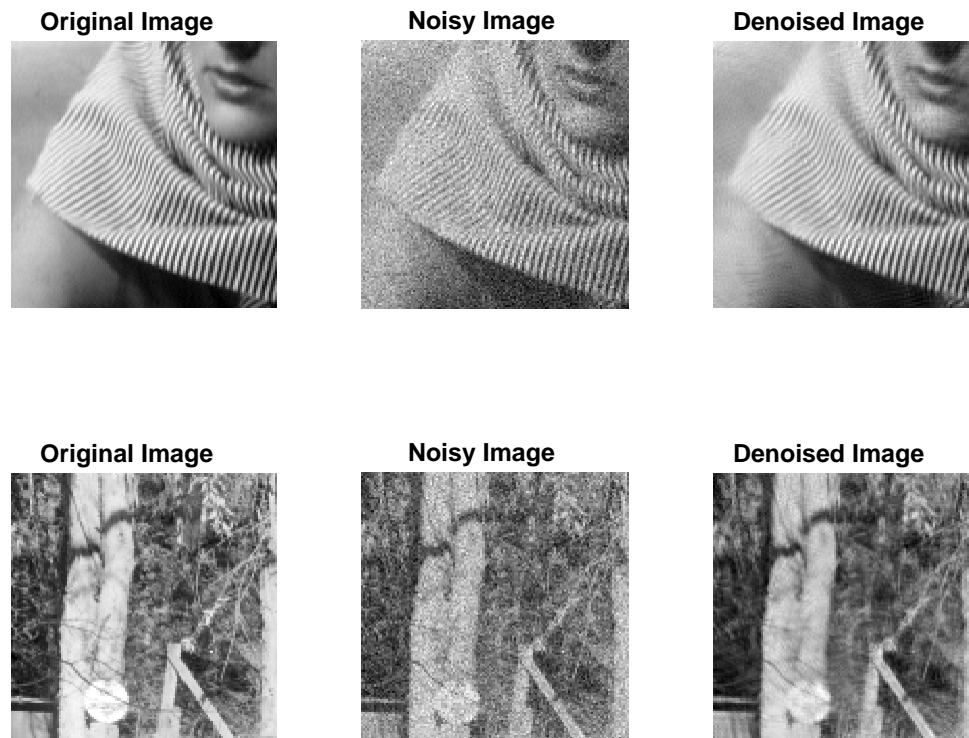
- RMSE of Noisy image: 0.023195
- RMSE of Denoised image: 0.015248

For Stream

- RMSE of Noisy image: 0.020759
- RMSE of Denoised image: 0.014852

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## 2. Part B



Pixel info: (X, Y) Pixel Value

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

For Barbara

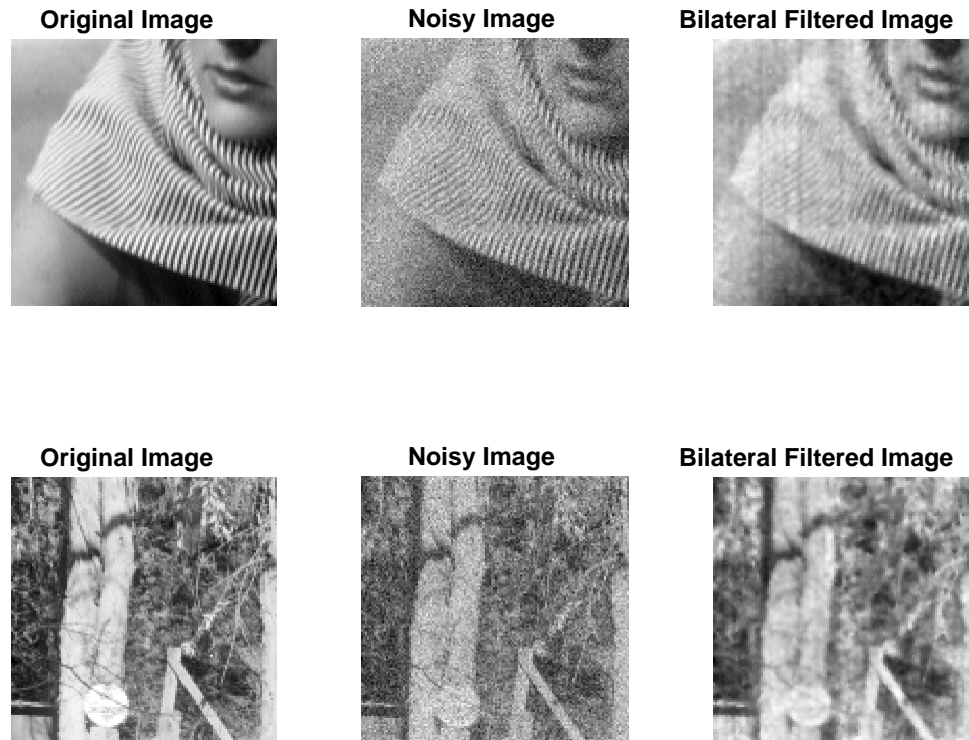
- RMSE of Noisy image: 0.022808
- RMSE of Denoised image: 0.011025

For Stream

- RMSE of Noisy image: 0.020791
- RMSE of Denoised image: 0.014297

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### 3. Part C



Pixel info: (X, Y) Pixel Value

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.

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## 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))**



Pixel info: (X, Y) Pixel Value

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

For Barbara

- Part a. RMSE of Noisy image: 0.0071941
- Part a. RMSE of Denoised image: 8.5976e-05
- Part b. RMSE of Noisy image: 0.0076732
- Part b. RMSE of Denoised image: 0.0074286

a. Original Image  
(poissrnd(im))



a. Noisy Image  
(poissrnd(im))



a. Denoised Image  
(poissrnd(im))



Pixel info: (X, Y) Pixel Value

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

For Barbara

- Part a. RMSE of Noisy image: 0.0071941
- Part a. RMSE of Denoised image: 8.5976e-05
- Part b. RMSE of Noisy image: 0.0076732
- Part b. RMSE of Denoised image: 0.0074286

Comparison between  $\text{poissrnd}(im)$  and  $\text{poissrnd}(im/20)$ :

- The latter actually represents image acquisition with a lower acquisition time and hence lower brightness.
- We observe that denoising is highly successful 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  $I(\text{signal variable})$  tends to infinity. Here we have drastically downscaled the pixel intensities leading to errors in the modelling assumption.

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## 5. Part E

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

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