Ashutosh Sharma (190100027)
Kritti Sharma (180100060)
Shreyas Chandgothia (180260037)

Homework Assignment 5
CS 663: Digital Image Processing

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Exercise 1

Figure 1: The original Barbara (*left*) and Stream (*right*) images given to us in the problem statement. Note that the whole Barbara image of size 256 by 256 has been considered. For the Stream image, only the top left 256 by 256 sub-portion of the image has been considered.

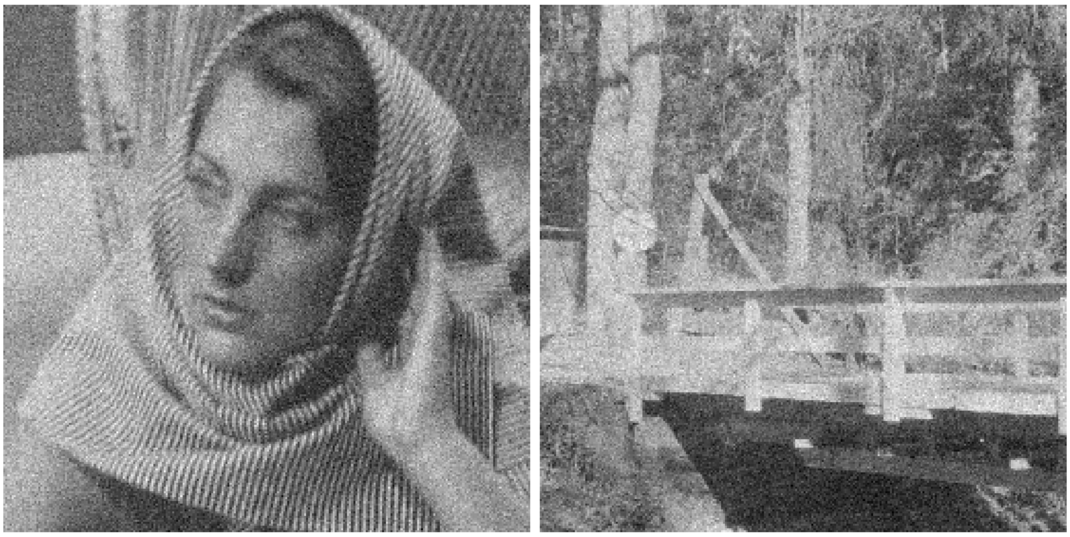

Figure 2: Barbara (*left*) and Stream (*right*) images corrupted with Gaussian noise having mean $\mu = 0$ and standard deviation $\sigma = 20$. The effect of noise addition is clearly visible in the two images. The fractional $RMSE$ values for these noisy images in comparison to the original noise-free images are as follows: $RMSE_{barbara} = 14.7\%$, $RMSE_{stream} = 12.6\%$

Part (a)

Figure 3: Resultant Barbara (*left*) and Stream (*right*) images (corrupted with Gaussian noise), after being processed using the $myPCADenoising1.m$ function. The denoising effect is clearly visible in these two images, although one can still perceive some amount of grainy noise. The fractional $RMSE$ values for these processed images in comparison to the original noise-free images are as follows: $RMSE_{barbara} = 7.1\%$, $RMSE_{stream} = 7.7\%$ (which are considerably lesser than the RMSE values for the input noisy images).

Part (b)

Figure 4: Resultant Barbara (*left*) and Stream (*right*) images (corrupted with Gaussian noise), after being processed using the $myPCADenoising2.m$ function. The denoising effect in this part is significantly better than the previous one, implying that selecting only similar patches during the PCA algorithm gives better results rather than selecting all patches globally. Most of the grainy noise has been effectively filtered out. The fractional $RMSE$ values for these processed images in comparison to the original noise-free images are as follows: $RMSE_{barbara} = 5.7\%$, $RMSE_{stream} = 7.3\%$ (which are better as compared to the previous part).

Part (c)

Figure 5: Resultant Barbara (*left*) and Stream (*right*) images (corrupted with Gaussian noise), after being processed using the $myBilateralFilter.m$ function from Homework 2, with parameters ($\sigma_s = 15$, $\sigma_r = 20$). We can observe that some amount of smoothing and denoising has taken place, in comparison to the noisy input images. However, the result using the bilateral filter is clearly sub-optimal when compared to the PC-based denoising in the previous two parts. The fractional $RMSE$ values for these processed images in comparison to the original noise-free images are as follows: $RMSE_{barbara} = 12.0\%$, $RMSE_{stream} = 10.6\%$ (which are higher as compared to both the previous parts).

The major difference between the PCA-based filtering and bilateral filtering lies in the underlying theory. A bilateral filter is a spatial filter which mainly eliminates high frequency noise to create a smoothing effect, at the expense of blurring fine details and sharp edges. On the other hand, the PCA-based technique relies on statistical methods, with the aim of overwriting noise by finding multiple similar patches to each patch in consideration and evaluating the average local statistics. This has better potential to preserve sharp features in the image and reduce the noise at the same time.

Part (d)

Clamping the values in the noisy image 'im1' to the [0,255] range is not the correct approach owing to the fact that the noise added to the image has a standard deviation of 20. This implies that over ∼95% of the noise values will be in the range $[-60, 60]$. Therefore, clipping the values below 0 and above 255 will severely affect the noise distribution and the assumption of Gaussian noise distribution will no longer be valid. Since the presence of Gaussian noise is a central assumption in the PCA-based filtering technique, the final resultant images would not be denoised correctly.