CS663, Assignment 5 **Yash Sanghvi, Pradyot Prakash**
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Question 1

(a) PCA based Denoising (I)

Explanation and Implementation Details

- We obtain overlapping, 7 X 7 size patches and reshape them into a 49 X 1 column vectors ($\overline{p_i}$) and hence form the matrix P =[$\overline{p_1}$ $\overline{p_2}$ ... $\overline{p_N}$].
- Then we obtain the eigenvector matrix $V = PP^T$. The Eigenvector coefficient vector for patch $\overline{p_i}$ is obtained by $\alpha_i = V^T\overline{p_i}$
- Once the eigencoefficients are obtained, $\overline{\alpha_j^2}$ is calculated for all j and the the eigencoefficients are updated according to Weiner Filter update: $\alpha_{ij}^{denoised} = \frac{\alpha_{ij}}{1+\frac{\sigma^2}{\overline{\alpha_j^2}}}$
- With the updated eigencoefficients, we reconstruct patches using $\overline{p_i^{denoised}} = V\alpha_i^{denoised}$
- To reassemble patches to form the image, we use overlap and add technique i.e We initially take an image array of all zeros and add the reconstructed patches to their original positions. Simultaneously, we keep a count on entire image of how many patches have covered a particular pixel. We ultimately divide the final image value by this count for each pixel individually to obtain the denoised image.

(b) PCA based Denoising (II)

Explanation and Implementation Details

The implementation of PCA based denoising here is the same as the previous part except the contruction of eigenspaces. Here for each patch $\overline{p_i}$, we obtain the 200 most similar patches $\overline{q_i}$ for i = 1,2,3,...,200 (obviously contains $\overline{p_i}$ as well) and construct the eigenspace of Q where Q = [$\overline{q_1}$ $\overline{q_2}$ $\overline{q_3}$ ... $\overline{q_{200}}$].
Now we obtain the eigencoefficeints of $\overline{p_i}$ based on this eigenspace and also calculate the $\overline{\alpha_j^2}$ based on the the eigencoefficients on the pathces $\overline{q_1}$,$\overline{q_2}$,..., $\overline{q_{200}}$. We update the eigencoefficients of the patch $\overline{p_i}$ based on the weiner filter update and reconstruct the patch using the eigenspace (as done previously). Note that the eigenspace used here changes with each patch unlike previously where the eigenspace was common for all the patches.

Results

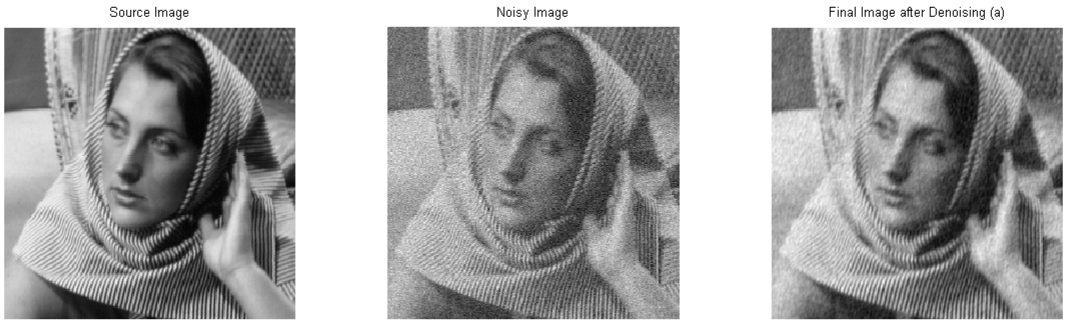

Figure 1: Source Image (Left), Noisy Image (Center) and Denoised Image using Weiner Filter update (first method). Error between Noisy image and Source Image: 19.94. Error between Denoised image and Source Image: 9.82

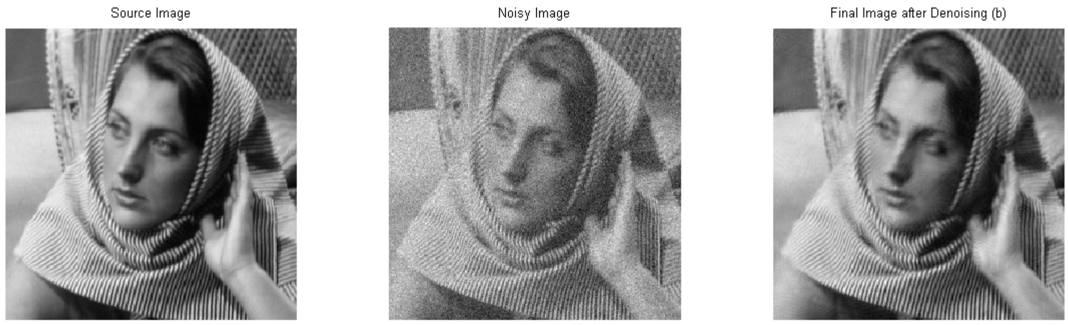

Figure 2: Source Image (Left), Noisy Image (Center) and Denoised Image using Weiner Filter update (second method). Error between Noisy image and Source Image: 19.94. Error between Denoised image and Source Image: 7.82

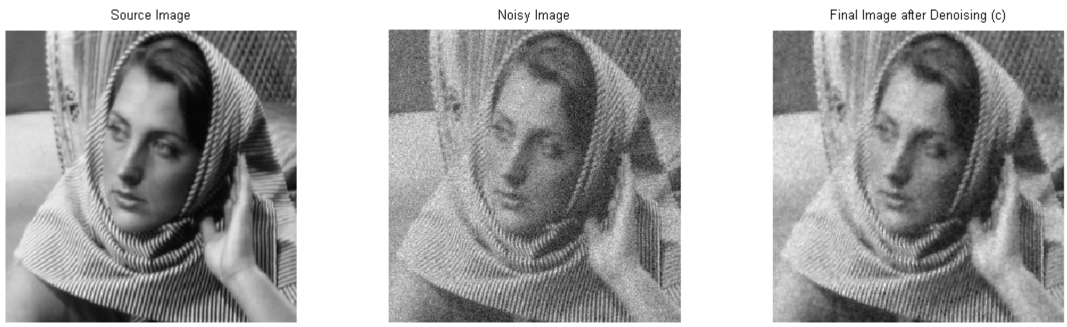

Figure 3: Source Image (Left), Noisy Image (Center) and Denoised Image using Bilateral Filtering. Error between Noisy image and Source Image: 19.94. Error between Denoised image and Source Image: 11.4004

Comments on Results

- The second method of PCA Denoising which involves calculating eigenspace for each patch using the closest 200 patches in the neighborhood is more effective here. The error is reduced by almost 60% whereas it is reduced by almost 50% in the first method. However, the second method is more computationally expensive.
- Bilateral Filtering is the least efficient for filtering compared to the other two methods. The optimal parameters for obtaining the least RMSD between the bilateral filtered image and the original image were ($\sigma_s = 0.99, \sigma_r = 48.4$) using a gaussian window of size 5 X 5.