Image Processing Assignment-2

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***Abstract*—This paper explores image restoration techniques. Full inverse filtering, Truncated inverse filtering, Weiner filtering and Constrained Least Square filtering methods are implemented.**

Keywords—filter, kernel, Weiner, Least Square, truncated

I. Introduction

In this assignment, image restoration techniques were applied to images blurred by space variant kernels. These kernels simulate real world camera shakes. The degradation is not severe and hence applying techniques which assume space invariance should give us reasonably good outputs.

II. Background Read

The understanding of this project requires us to have basic understanding of some concepts of image processing image restoration, and MATLAB. Basic mathematical concepts like exponent and matrix operations should be known.

III. Method

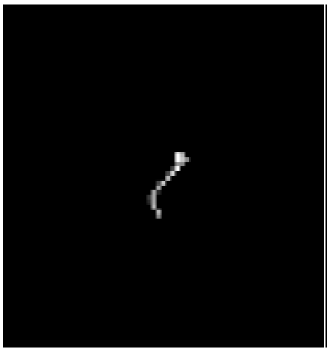
Kernel images were downloaded from [1], and then cropped to get spatially invariant kernels

1. Original Image:

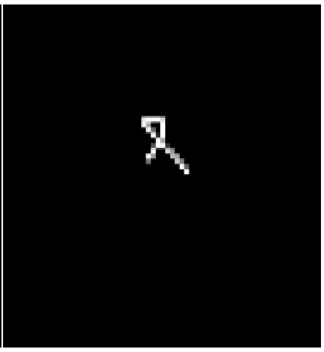
The original image without degradation is:

2. Kernels:

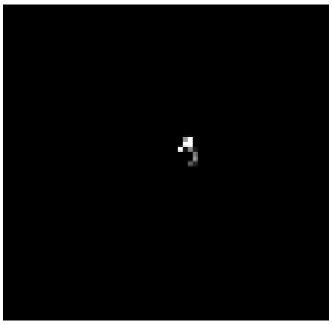
The kernels obtained are:



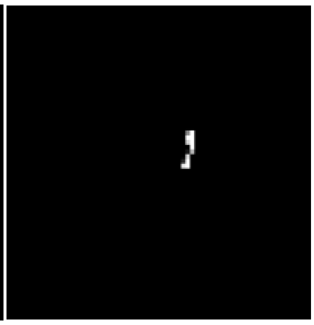
Kernel 1



Kernel 2



Kernel 3



Kernel 4

A. Full Inverse Filtering:

The kernels were padded with zeros to make its size equal to that of the image. DFT of the images were taken. The DFT of the output was obtained by dividing the DFT of the image by DFT of the Kernel. Then IDFT is taken to find the final image.

B. Truncated Inverse Filtering:

The DFT of the preliminary output was obtained by dividing the DFT of the image by DFT of the Kernel. The resultant DFT values above a certain aforementioned value of radius are made 1, and then IDFT is taken to get the final output.

C. Weiner Filtering:

Let G(u, v) be the DFT of the blurred image, F(u, v) be the DFT of the original image and H(u, v) be the DFT of the kernel, then the DFT of the MMSE is:

$$\hat{F}(u,v) = \frac{H^*(u,v)G(u,v)}{|H(u,v)|^2 + K}$$

K is varied to get to the best image.

D. Constrained Least Squares Filtering:

Let the edge matrix be

$$p(x,y) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

The solution proposed by this method is:

$$\hat{F}(u,v) = \frac{H^*(u,v)G(u,v)}{|H(u,v)|^2 + \gamma|P(u,v)|^2}$$

The parameter γ is modified so as to maximize PSNR and SSIM.

IV. Results

1. Kernel 1:

Original

Blurred Image

Full Inverse Output

Truncated Inverse with r=100 PSNR=25.27 SSIM=0.9464

Weiner Filter with k=0.01 PSNR=32.05 SSIM=0.9875

CLSR with γ=0.0001 PSNR=44.07 SSIM=0.9986

2. Kernel 2:

Original

Blurred Image

Full Inverse Output

Truncated Inverse with r=100 PSNR=25.27 SSIM=0.9464

Weiner Filter with k=0.01 PSNR=31.22 SSIM=0.9840

CLSR with γ=0.0001 PSNR=45.81 SSIM=0.9991

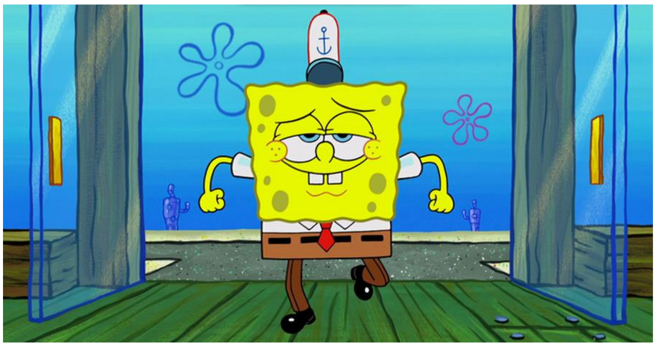
3. Kernel 3:

Original

Blurred Image

Full Inverse Output

Truncated Inverse with r=100 PSNR=25.27 SSIM=0.9464



Weiner Filter with k=0.01 PSNR=38.30 SSIM=0.9968

Full Inverse Output

CLSR with γ=0.001 PSNR=38.52 SSIM=0.9972

Truncated Inverse with r=100 PSNR=25.27 SSIM=0.9464

4. Kernel 4:

Original

Blurred Image

Weiner Filter with k=0.01 PSNR=34.68 SSIM=0.9914

CLSR with γ=0.0001 PSNR=45.88 SSIM=0.9989

V. CONCLUSIONS

The main conclusions we draw from the assignment are:
1. As the radius in the truncated inverse filter increases the PSNR reaches maxima after which it decreases again.
2. CLSR and Weiner filters perform much better than their full inverse and truncated inverse counterparts.

VI. REFERENCES

[1] http://webdav.is.mpg.de/pixel/benchmark4camerashake/
[2] Rafael C. Gonzalez, Richard E. Woods-Digital Image Processing-Prentice Hall