Image Restoration

Aryan Agal
Department of Energy Science and Engineering
Indian Institute of Technology, Bombay
Mumbai, India
aryanagal@iitb.ac.in

***Abstract*—This project implements some basic image deblurring algorithms introduced in class. An interface to conveniently access all functionality was also designed.**

Keywords—deblur, restoration, frequency filtering, image processing, algorithms

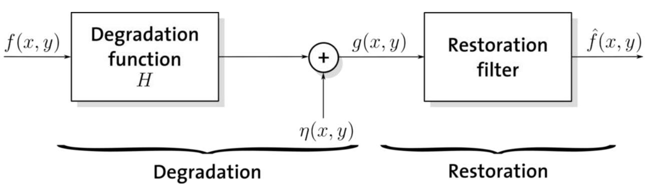
I. Introduction

The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus. In cases like motion blur, it is possible to come up with an very good estimate of the actual blurring function and "undo" the blur to restore the original image. In cases where the image is corrupted by noise, the best we may hope to do is to compensate for the degradation it caused. In this project, we will introduce and implement several of the methods used in the image processing world to restore images. This assignment implements an image editor using MATLAB 2018a software.

II. Background and Related Work

Images are often degraded during the data acquisition process. The degradation may involve blurring, information loss due to sampling, quantization effects, and various sources of noise. The purpose of image restoration is to estimate the original image from the degraded data. Applications range from medical imaging, astronomical imaging, to forensic science, etc. Often the benefits of improving image quality to the maximum possible extent far outweigh the cost and complexity of the restoration algorithms involved.

The basic model of image degradation has the original image f (x,y) convoluted with the degradation function h(x,y). Noise η(x,y) is assumed to be additive and random. The degraded image g(x,y) is obtained as:



The frequency domain equivalent of the degradation model is:

$$G(u,v) = H(u,v)F(u,v) + N(u,v)$$

Our model of degradation admits two contributors to degradation - the degradation model and the random noise. For a given image the degradation can be caused by any one or both of these factors.

There are many existing images of unique events that can-not be retaken that we would like to be able to. Another application in medical imaging: it is preferable to avoid retaking a blurred x-ray, in order to safeguard the patient's health. Cost is another argument for using restoration for many applications. High quality optics, sensing equipment, and hardware corrections are expensive.

III. Image Restoration Techniques

A. Direct Inverse Filtering

Inverse filtering is the quickest and easiest way to restore the blurred figure if a good model of the blurring function that despoiled an image is known or can be developed. Blurring can be measured as low pass filtering in inverse filtering technique we use high pass filtering action to reconstruct the blurred image without much effort.

B. Truncated Inverse Filtering

This method is an improvement over the naive inverse filtering and modifies the filtering process by suppressing all the high frequency components of the image. This method applies a low pass filter after direct inverse filtering in order to filter the noise out.

C. Weiner Filter deblurring technique

Weiner filter is a standard image restoration approach proposed by N. Weiner that incorporates both the degradation purpose and statistical characteristic of noise into the restoration function. Weiner Filtering is also a non-blind procedure for reconstructing the degraded image in the presence of known PSF. It removes or reduces to some amount the additive noise and inverts the blurring simultaneously. Weiner filter not only implied the deconvolution by inverse filtering (elevated pass filtering) but also removes the noise with a compression operation (low pass filtering).It compares amid an assessment of the noiseless image we want or desired. The input to a weiner filter is a degraded figure corrupted by additive noise.

D. Impulse Noise Reduction Filters

The images corrupted by impulse noise are often occurred in practice. This type of noise may show in digital images because of channel decoder damages, dyeing down of signal in communication links, communication subscriber's moving, video sensor's noises.Applying of classic median filter for removal of such kind of noise gives relatively good results,which are shown in restoring of brightness drops, object edges and local peaks in noise corrupted images.But analysis of different sources dedicated to median filtering gives, that the classic median filter has a set of disadvantages:

-signal weakening (object's counters and edges are blurred in figure);

-affect to non corrupted ("good") image pixels.

E. *Median Filter*

Median filter, the most significantly used impulse noise removing filter, provides better removal of impulse noise from corrupted figures by replacing the individual pixels of the figure as the name suggests by the median value of the gray level of the pixels from a selected neighborhood. The median of a set of values is such that half of its values in the set are under the median value and half of them are above it and so is the most acceptable value than any other image statistics value for replacing the impulse ruined pixel of a noisy image for if there is an impulse in the set chosen to determine the median it will firmly lie at the ends of the set and the chance of Identifying an impulse as a median to replace the image pixel is very fewer. For a current image f which is noisy, the median filter is a sliding square window of odd size that moves over the whole image, replaces individual pixel of the image by the median of all the pixels of the window

F. *Learning a Deep Convolutional Network for Image Super-Resolution(SRCNN)*

A convolutional neural network is presented for image super-resolutions. The network directly learns an end-to-end mapping between low and high resolution image, with little pre/post-processing beyond the optimization. A relation is established between traditional sparse-coding-based SR methods and deep-learning based SR method.

G. *CNN Denoiser Prior for Image Restoration*

This technique aims to train a set of fast and effective CNN denoisers and integrate them into model-based optimization methods to solve other inverse problems. Experimental results demonstrate that the learned set of denoisers can not only achieve promising Gaussian denoising results but also can be used as prior to deliver good performance for various low-level vision applications.

H. *Noise2Noise: Learning Image Restoration without Clean Data*

They apply basic statistical reasoning to signal reconstruction by machine learning – learning to map corrupted observations to clean signals – with a simple and powerful conclusion: it is possible to learn to restore images by only looking at corrupted examples, at performance at and some-times exceeding training using clean data, without explicit image priors or likelihood models of the corruption. In practice, they show that a single model learns photographic noise removal, denoising synthetic Monte Carlo images, and reconstruction of undersampled MRI scans – all corrupted by different processes – based on noisy data only.

I. *Image Restoration and Reconstruction using Variable Splitting and Class-adapted Image Priors*

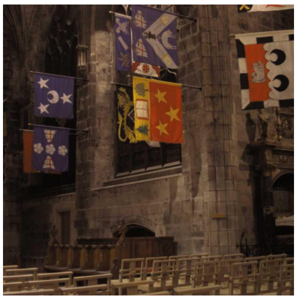
This paper proposes using a Gaussian mixture model as a prior, for solving two image inverse problems, namely image deblurring and compressive imaging. They capitalize on the fact that variable splitting algorithms, like ADMM, are able to decouple the handling of the observation operator from that of the regularizer, and plug a state-of-the-art algorithm into the pure denoising step. Furthermore, they show that, when applied to a specific type of image, a Gaussian mixture model trained from an database of images of the same type is able to outperform current state-of-the-art methods.

IV. Experiments and Results

Testing was done for all the images on all 4 required methods. Some results can be seen below.

In general the images were well deblurred when working with the gamma filter. A few results are given in the next page. The images selected were as follows

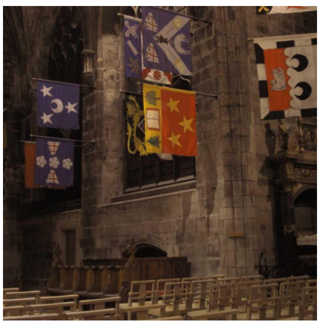
A. *Church*



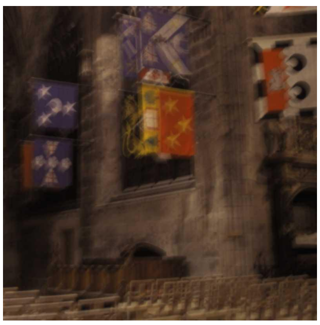
B. *Clock*

C. *Backyard*

D. *Roof*



Ground Truth



Blurry

Ground Truth

Blurry

Full Inverse: SSIM-0.30713
PSNR-16.001

Truncated Inverse: r=0.194
SSIM-0.194 PSNR-18.015

Full Inverse:
SSIM-0.0794 PSNR-11.116

Truncated Inverse: r=0.203
SSIM-0.346 PSNR-12.73

Weiner Filter: K=18
SSIM-0.625 PSNR-18.19

Gamma Filter: Gamma=12
SSIM-0.621 PSNR-18.138

Weiner Filter: K=82
SSIM-0.405 PSNR-13.002

Gamma Filter: Gamma=27
SSIM-0.384 PSNR-12.877

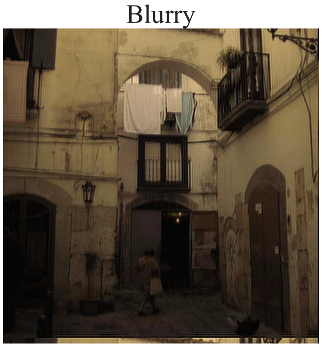
Ground Truth

Blurry

Ground Truth

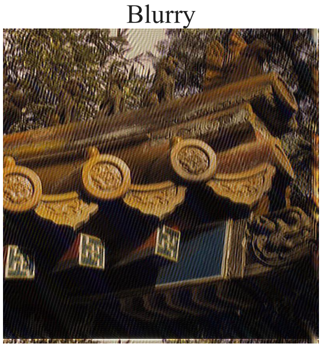
Blurry

Full Inverse:
SSIM-0.429 PSNR-16.087



Truncated Inverse: r=0.251
SSIM-0.748 PSNR-18.675

Full Inverse:
SSIM-0.233 PSNR-11.979



Truncated Inverse: r=0.288
SSIM-0.389 PSNR-13.407

Weiner Filter: K=23
SSIM-0.751 PSNR-18.264

Gamma Filter: Gamma=16
SSIM-0.757 PSNR-18.457

Weiner Filter: K=3
SSIM-0.482 PSNR-13.456

Gamma Filter: Gamma=3
SSIM-0.495 PSNR-13.521

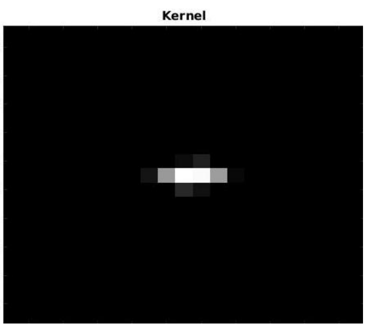
V. Blur Kernel Estimation and Deblurring

To do the last part of the assignment I have used the method proposed by Krishnan et al.[10], on an image of the first day at my current hostel.

Original

Restored

Detected Point Spread Function(PSF)(21x21)



Most of the image remained seemingly unchanged, but a little part of the tree leaves became slightly outlined.

VI. Discussion and Conclusions

With the blur kernel available, the problem of attaining the original, deblurred is a very straightforward problem and has been sufficiently solved. With our experiments, gamma filter and weiner filter seem to be working much better than the truncated inverse as well as inverse filters. Clearly the inverse filter amplifies a lot of noise which is avoided with the truncated inverse filter. The more challenging task lies ahead of us, where we don't have the blur kernel with us. Such blind deblurring methods have been working particularly well in the era of deep learning, especially.

VII. Acknowledgment

I would like to thank Prof. Amit Sethi of the Electrical Engineering Department, for giving me an opportunity to work on this project. I would also like to thank Nikhil Cherian for his guidance.

VIII. Relevant Links

The code and report are available on GitHub.

IX. References

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