International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2015): 6.391

Linear Filtering Based Image Restoration with Image De-Blurring Toolkit

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Abstract: ***Wiener filter model an image patch as a linear combination of a few atoms chosen out from an over-complete dictionary and they have shown promising results in various image restoration applications. To improve the performance of filtering noise is introduced, and the goal of image restoration turns to how to suppress the noise. The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. Blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Simultaneous wiener is proposed as a framework for combining these two approaches in a natural manner, achieved by jointly decomposing groups of similar signals on subsets of the learned dictionary. It imposes that similar patches share the same dictionary elements in their filter decomposition. Image restoration intends to recover high resolution image from low resolution image. Blurring is a process of reducing the bandwidth of an ideal image that results in imperfect image formation. Image restoration concerned with the reconstruction of uncorrupted image from a blurred or noise one. It is difficult to design a standard model for digital camera noise.***

Keywords: Image restoration, nonlocal similarity, sharpening, filtering, de-blurring, de-noising

1. Introduction

Sparse representation models code an image patch as a linear combination of a few atoms chosen out from an over-complete dictionary, and they have shown promising results in various image restoration applications. However, due to the degradation of the observed image (e.g., noisy, blurred, and/or down-sampled), the sparse representations by conventional models may not be accurate enough for a faithful reconstruction of the original image. To improve the performance based image restoration; in this the Wiener filter purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

1) Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross correlation.
2) Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).
3) Performance criteria: Minimum mean-square error.

1.1. Blur image


(a)Original image


(b) Blurred image

In image terms blurring means that each pixel in the source image gets spread over and mixed into surrounding pixels. Another way to look at this is that each pixel in the destination image is made up out of a mixture of surrounding pixels from the source image.

2. Literature Survey

A new fast and efficient algorithm capable in removing Gaussian noise with less computational complexity is presented. The algorithm initially estimates the amount of noise corruption from the noise corrupted image. In the second stage, the center pixel is replaced by the mean value of the some of the surrounding pixels based on a threshold value. Noise removing with edge preservation and computational complexity are two conflicting Parameters. The proposed method is an optimum solution for these requirements. The performance of the algorithm is tested and compared with standard mean filter, wiener filter, Alpha trimmed mean filter K- means filter, bilateral filter and recently proposed trilateral filter. Experimental results show the superior performance of the proposed filtering algorithm compared to the other standard algorithms in terms of both subjective and objective evaluations. The proposed method removes Gaussian noise and the edges are better preserved with less computational complexity and this aspect makes it easy to implement in hardware [1].The attempts to undertake the study of three types of noise such as Salt and Pepper (SPN), Random variation Impulse Noise (RVIN), Speckle (SPKN). Different noise densities have been removed between 10% to 60% by using five types of filters as Mean Filter (MF), Adaptive Wiener Filter (AWF), Gaussian Filter (GF), Standard Median Filter (SMF) and Adaptive Median Filter (AMF). The same is applied to the Saturn remote sensing image and they are compared with one another. The comparative study is conducted with the help of Mean Square Errors (MSE) and Peak Signal to Noise Ratio (PSNR).So as to choose the base method for removal of noise from remote sensing image. Digital image processing is the most important technique used in remote sensing. It has helped in the access to technical data in digital and multi-wavelength, services of computers in terms of speed of processing the data and the possibilities of big storage [2]. Adaptive Wiener Filter (AWF) changes its behavior based on the statistical Characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. But the improved performance is at the cost of added filter complexity. Mean and variance are two important statistical measures using which adaptive filters can be designed [2]

2.1 Advantages

- Proposed method shows superior performance for the datasets that consists of several challenging bad quality images, compared with other techniques.
- It is simple, robust, and involves minimum parameter tuning.
- Ability to produces a binary results with better visual quality and contains most of the image information.
- Filters re-evaluate the value of every pixel in an image. For a particular pixel, the new value is based of pixel values in a local neighbourhood, a window centred on that pixel,in order to:
  -Filters provide visual interpretation of images.
  -It can also be used as a precursor to further digital processing, such as segmentation.
- Filters may either be applied directly to recorded images, after transformation of pixel values.
- Filters are linear if the output values are linear combinations of the pixels in the original image, otherwise they are nonlinear.
- Linear filters are well understood and fast to compute, but are incapable of smoothing

3. Related Work

The inverse filtering is a restoration technique for deconvolution, when the image is blurred by a known low pass filter; it is possible to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)},$$

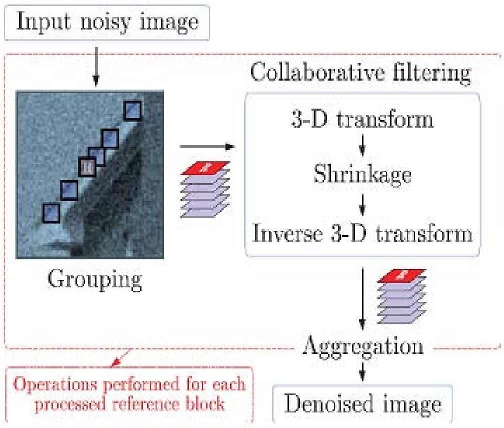

Figure 1: Filter Technique

Collaborative filtering for image de-noising algorithm involves 2 steps:
1. Block estimate: In step one Block wise estimate is done for grouping and thresholding which follows aggregation.
2. Final estimate: In step two Block wise estimates is done for grouping and filtering which also follows aggregation.

3.1 How to blur an image

- Traverse through entire input image array.
- Read individual pixel color value (24-bit).
- Split the color value into individual R, G and B 8-bit values.
- Calculate the RGB average of surrounding pixels and assign this average value to it.
- Repeat the above step for each pixel.
- Store the new value at same location in output image.

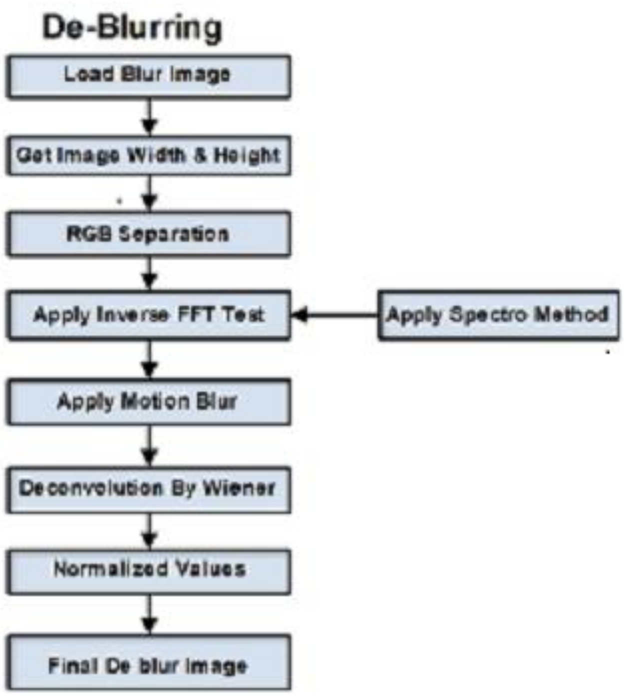

Figure 2: System Architecture

4. Implementation

4.1. Modules

4.1.1 Image Blur motion

In motion blur, any object moving with respect to the camera will look blurred or smeared along the direction of relative motion. It takes blurred image as input captured by camera or any original image converts into blurred image. In blurring, we simple blur an image. An image looks sharper or more detailed if we are able to perceive all the objects and their shapes correctly in it. This smearing may occur on an object that is moving or on a static background if the camera is moving. In a film or television image, this looks natural because the human eye behaves in much the same way. Because the effect is caused by the relative motion between the camera, and the objects and scene, motion blur may be avoided by panning the camera to track those moving objects. In this case, even with long exposure times, the objects will appear sharper, and the background more blurred.

4.1.2 Image De blur:

De blurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. The blur is typically modeled as the convolution of a (sometimes space- or time-varying) point spread function with a hypothetical sharp input image, where both the sharp input image (which is to be recovered) and the point spread function are unknown. This is an example of an inverse problem. In almost all cases, there is insufficient information in the blurred image to uniquely determine a plausible original image. In addition the blurred image contains additional noise which complicates the task of determining the original image. This is generally solved by the use of a regularization term to attempt to eliminate implausible solutions. Load the blur image & output is the de blur image.

4.1.3 image processing_Blur 5x5

May be the results are not much clear. Let's increase the blurring. The blurring can be increased by increasing the size of the mask. The more is the size of the mask, the more is the blurring. Because with greater mask, greater number of pixels are catered and one smooth transition is defined. Input blurred image is converted into 5x5 masks, the result of a mask of 5x5 on an image is found out here.

4.1.4 Image Sharpening:

Human perception is highly sensitive to edges and fine details of an image, and since they are composed primarily by high frequency components, the visual quality of an image can be enormously degraded if the high frequencies are attenuated or completed removed. In contrast, enhancing the high-frequency components of an image leads to an improvement in the visual quality. Image sharpening refers to any enhancement technique that highlights edges and fine details in an image. Image sharpening is widely used in printing and photographic industries for increasing the local contrast and sharpening the images.

4.2Algorithm

4.2.1 Wiener Filter

It takes a statistical approach to solve its goal. Goal of the filter is to remove the noise from a signal. Before implementation of the filter it is assumed that the user knows the spectral properties of the original signal and noise. Spectral properties like the power functions for both the original signal and noise. And the resultant signal required is as close to the original signal. Signal and noise are both linear stochastic processes with known spectral properties. The aim of the process is to have minimum mean- square error. That is, the difference between the original signal and the new signal should be as less as */-/////ypossible.

Equations:

Input: Blurred image

Output: Deblurred image

I) considering we need to design a wiener filter in frequency domain as W (u, v).
II) Restored image will be given as; X n (u, v) = W (u, v).Y (u, v) Where Y (u, v) is the received signal and X n (u, v) is the restored Image.
III) Considering images and noise as random variables, Compute f of the uncorrupted image f s u mean square error between them is minimized. We choose The error measure is given by W (k, l) to minimize: e 2 = E {(f − f)2 }
IV) H (u, v) = degradation function.
| H (u, v)|^2 = H*(u, v) H (u, v).H*(u, v) = complex conjugate of H (u, v).
S n (u, v) = |N (u, v)|^2 power spectrum of noise.
S f (u, v) = |F (u, v)|^2 power spectrum of undegraded image.
G (u, v) is the transform of the degraded image.

4.2.2 Algorithm for Image Deblurring

Step 1: We take original image as input image.
Step 2: original image is then convoluted into with PSF. PSF is obtained by Amplitude phase function (APF).extract height & width.
Step 3:apply Inverse FFT forward Test.
Step 4: Convoluted output is added with motion blur
Step 5 : Apply motion blur we get blur images.
Step 6 : The output of blurry image is then de-convolution by Wiener.
Step 7: After de-convoluted we get the de-blurred image.

5. Experimental Results

To illustrate the Wiener filtering in image restoration using the standard test image. Blur the image with the low pass filter. Then put into the blurred image the additive white Gaussian noise of variance 100. The Wiener filtering is applied to the image with a cascade implementation of the noise smoothing and inverse filtering. The images are listed as follows together. Notice that the restored image is improved in terms of the visual performance. It is easy to see that the Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. Here for image de blurring use FFT algorithm, It not only performs the deconvolution by inverse filtering (high pass filtering) but also removes the noise with a compression operation (low pass filtering). 5x5 window matrix is used to sharpening the image. Due to the limited page space, we only show part of the results.

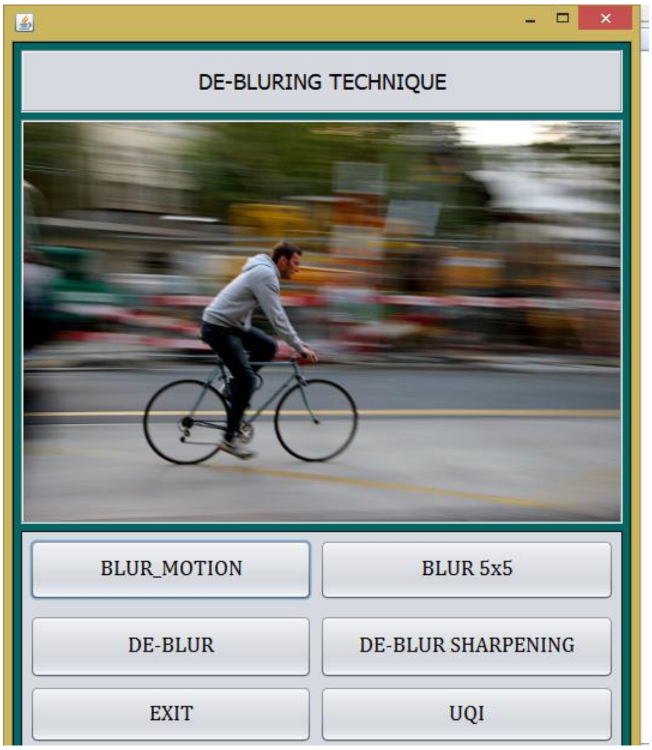

Figure 4: Blurring Technique

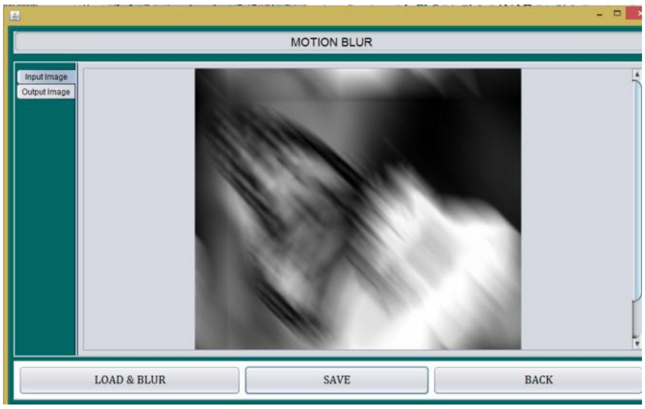

Figure 5: module 1

Figure 6: module 2

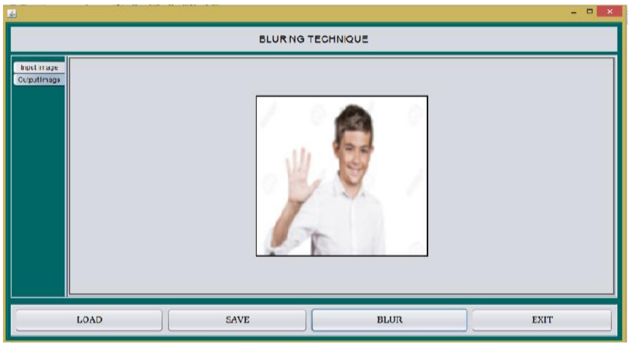

Figure 7: module 3

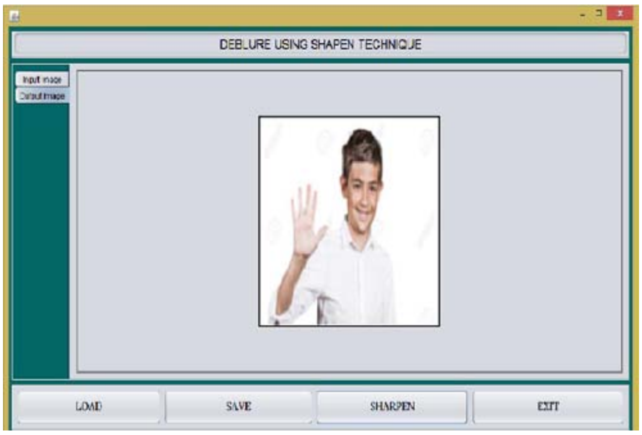

Figure 8: module 4

Figure 9: Quality measures

5.1Wiener Filtering and Image Processing

The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. From a signal processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be intensities from points along the line of the camera's motion. This is a two-dimensional analogy to

$$G(u,v)=F(u,v).H(u,v)$$

Where F is the Fourier transform of an "ideal" version of a given image, and H is the blurring function. In this case H is a sync function: if three pixels in a line contain info from the same point on an image, the digital image will seem to have been convolved with a three-point boxcar in the time domain. Determination of a good blurring function requires lots of trial and error. Second, inverse filtering fails in some circumstances because the sync function goes to 0 at some values of x and y. Real pictures contain noise which becomes amplified to the point of destroying all attempts at reconstruction of Fest.

The best method to solve the problem is to use Wiener filtering. This tool solves an estimate for F according to the following equation:

$$Fest(u,v) = |H(u,v)|^2.G(u,v)/(|H(u,v)|^2.H(u,v) + K(u,v))$$

Figure 10: Reconstructed photograph, e.g. festimate, through Wiener filtering

6. Conclusion

In the introduction, the FFT & Wiener filter is used to reduce the amount of blurr presented in a images by comparison with an estimation of the desired deblurred images. It can be observed in the results, the image restoration is not absolutely perfect but it achieves a very close image to the original one. However, if it is necessary to find a value to perform the closest restoration, the invested time is very high, which can be a problem in many cases.

7. Acknowledgement

I would like to express my sincere gratitude to my guide Prof. Shivale Nitin for his continuous support, patience,motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this paper.

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