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A Wavelet based approach for Image Deblurring

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Abstract

Images are often degraded during the data acquisition process. One of the factors involved in image degradation is blurring. Restoring the images from such degraded observation is an important issue in image processing. Number of techniques has been proposed in the past to encounter such problems. But, they involve complex computations and methods. So, new simple but more effective methods are needed for de-blurring the images. In this paper, a new approach using wavelet transform is presented for restoration of such blurred images. The method is very simple, effective and robust and produces good results.

Keywords: Imaging, wavelet transform, deblurring, PSNR

Introduction

Images are created to record or display useful information. These recorded images perpetually represent a degraded version of the original scene due to faults in the imaging and capturing process[1]. The undoing of these faults is necessary to improve the quality of the image so as to make them suitable for many of the subsequent image processing tasks.

A wide range of different degradations exist in practical applications. A few instances are geometrical degradations illumination, color imperfections and blurring. Blurring is a form of bandwidth diminution of an ideal image owing to the imperfect image formation process[2]. It can be caused by an optical system that is out of focus, or by relative motion between the camera and the original scene as in the case of aerial photographs produced for remote sensing purposes. It may also be caused by aberrations in the optical system and atmospheric turbulence. Some known examples of existence of such blurring are the corruption caused by spherical aberrations of the electron lenses and that due to X-ray scattering in CT scans.

The purpose of image restoration is to estimate or recover the scene without image degradation or distortion caused by non ideal image system. The blur distortion is reduced or removed using deblurring. This work introduces a wavelet based degradation approach of image Deblurring and tested it on various bench marked images.

Review of Existing Approaches

In most recent work, image blur is modeled as the convolution of an unobserved latent image with a single, spatially invariant blur kernel. Despite image blur arises from multiple causes, image blur due to camera motion has recently received increased attention, as it is a common problem in consumer-level photography. Addressing this blur problem through deblurring is considered important in the computer vision community. Basically, deblurring is the combination of two tightly coupled sub-problems: PSF estimation and non-blind image Deconvolution. These problems have been addressed both independently and jointly[3]. Both are longstanding problems in computer graphics, computer vision, and image processing.

Software-based methods[4, 5]) use image priors and kernel priors to constrain an optimization for the blur kernel and the latent image. Shan et al [4] incorporated spatial parameters to enforce natural image statistics using a local ringing suppression step. Fergus et al[5] recovered a blur kernel by using a natural image prior on image gradients in a variational bayes framework. Jia[6] used transparency maps to get cues for object motion to recover blur kernels by performing blind-deconvolution on the alpha matte, with a prior on the alpha-matte.

Another type of work involved segmenting the image and applying deblurring separately for each segment with the idea that different segments have different blur. Levin et al[7] and Cho et al [8] segmented images into layers where each layer had a different motion blur.

Both the above approaches considered uniform object motion, but not non-uniform ego-motion (of the camera). Joshi et al.[9] predicted a sharp image consistent with an observed blurred image. They then solved for the 2D kernel that maps the blurred image to the predicted image. Tai et al.[10,11] developed a hybrid camera which captured a high frame rate video and a blurred image. Optical flow vectors from the video were used to guide the computation of spatially varying blur kernels which are in turn used for deblurring. This method is limited by the requirement of a hybrid camera and faces problems in regions where optical flow computation fails.

Ratnakar Dash[11] proposed two phase deblurring approach to get rid of the noise amplification in the restoration process. In the first phase, a novel detection method was proposed to find out the pixels affected by noise .Then the noisy pixels were filtered out. The filtered data was then used for deblurring in the second phase. The method was based on the second order difference among pixels in a test window to determine the noise status of the centre pixel. In the second phase, a new regularization technique was applied to handle the outliers still remained after first phase.

Background

3.1. Blurring

Blur is an unsharp image area caused by camera or subject movement, inaccurate focusing, or the use of an aperture that gives shallow depth of field. Blur effects are filters that make smooth transitions and decrease contrast by averaging the pixels next to hard edges of defined lines and areas where there are significant color transition. In digital images, there are 3 common types of Blur effects:

i. Average Blur
ii. Gaussian Blur
iii. Motion Blur

Average Blur

The Average blur is one of several tools we can use to remove noise and specks in an image. It is used it when noise is present over the entire image[12] . This type of blurring can be distributed in horizontal and vertical direction and can be circular averaging by radius R which is evaluated by the formula:

$$R = \sqrt{g2 + f2}$$

where g is the horizontal size blurring direction and f is vertical blurring size direction and R is the radius size of the circular average blurring.

Gaussian Blur

The Gaussian blur [13,14] is a type of image-blurring filters that uses a Gaussian function for calculating the transformation to apply to each pixel in the image. The equation of a Gaussian function in one dimension is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

In two dimensions, it is the product of two such Gaussians, one in each dimension:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where *x* is the distance from the origin in the horizontal axis, *y* is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. When applied in two dimensions, the Gaussian filter produces a surface whose contours are concentric circles with a Gaussian distribution from the center point. Values from this distribution are used to build a convolution matrix applied to the original image. The new value of each pixel is set to a weighted average of that pixel's neighborhood. The value of the original pixel receives the heaviest weight and neighboring pixels receive smaller weights as their distance to the original pixel increases.

Motion Blur

The Motion Blur[12, 15] is a filter that makes the image appear to be moving by adding a blur in a specific direction. This blur is introduced in the image due to the relative motion of the camera and the scene. The period of the exposure determined by the shutter speed of the camera may also cause this blur.

3.2 Image Deblurring

An image is degraded when it is blurred. To upgrade the image quality, deblurring is applied. Deblurring is an inverse problem to recover an image suffered from linear degradation. It has to cop up with both space variant and space-in variant deblurring. Image deblurring methods can be divided into two classes: non blind, in which the blurring operator like a PSF(Point Spread Function) is known and blind, in which the blurring operator is unknown. In both of these approaches, the image is restored from the blurred image. That is, an uncorrupted or less corrupted image is estimated from blurred and noisy one. A linear image restoration problem from blurring is also called as De-convolution. The advantages of De-convolution are higher resolution and better quality.

3.3 Wavelet Theory

The wavelet domain has attracted the researchers in many areas due to its various advantages. The discrete wavelet transform is mostly utilized since it is easier to implement in the computers.

Discrete Wavelet Transform

In signal processing, a transformation technique is used to project a data in one domain into another where some useful hidden information can be extracted. A wavelet transform is a lossless linear transformation of a signal or data into coefficients on a basis of wavelet functions[16]. It decomposes a signal into several groups of coefficients. These coefficient vectors contain information about characteristics of the data at different scales. Fine scales capture local details of the coefficients and coarse scales capture global features of a signal. Performing the discrete wavelet transform of a signal x is done by passing it through low pass filters (scaling functions) and high pass filters simultaneously. The result at each pass of the filtering of the signal is a convolution of the impulse response g of the filter and the signal. The frequency of the signal is halved after passing the signal through a filter. Since, by Nyquist's rule, half of the samples are enough to perfectly reconstruct the filtered signal, down-sampling or decimation by a factor 2 is performed to discard half of the samples. The down sampling involves removing every alternative coefficient in the function $y(n)$. The combined operation of filtering and down sampling for low pass and high pass filters can be mathematically expressed by the following two equations

$$y_{low}(n) = \sum_{k=-\infty}^{\infty} x[k].g[2.n-k]$$

$$y_{high}(n) = \sum_{k=-\infty}^{\infty} x[k].h[2.n-k]$$

In matrix form, wt =$[WX^T]^T$ where W =[L;H] where L and H are impulse responses of low pass and high pass filters and wt is wavelet transform of the input signal X. The two filters used at each stage of decomposition must be related to each other by $g[L-1-n] = (-1)^n.h[n]$ where g and h are the impulse responses of the two filters and L is such that $0 \le n < L$. These filters are known as quadrature mirror filters. The wavelet coefficients vector resulted from applying wavelet transform to a signal consists of both $y_{high}(n)$ (also called detailed coefficients) and $y_{low}(n)$ (also called approximation coefficients) coefficients in order.DWT proceeds further by recursively applying two convolution functions each producing an output stream that is half of the length of the original input. This process continues until the resolution (number of approximation coefficients) becomes one at which resolution level is said to be zero. Number of detailed coefficients at each level j is equal to $n/2^j$.The term 'scale' used in the context of wavelet transform at a level j is given by $\tau = 2^{j-1}$. Each detailed coefficient at a level tells us how much a weighted average of the data changes from a particular time period to next one. On the other hand, approximation coefficients are associated with averages of the data on scales $\tau_{J+1}\Delta t$ and higher where J is the largest level of wavelet decomposition for a signal and Δt is time interval between consecutive observations. The maximum level of decomposition depends on the wavelet function used for transformation. For example, the maximum level of decomposition of a signal x for Haar wavelet is given by $\log_2(x)$. Figure 1 depicts the entire process of DWT.

As shown in Figure 1, the number of data is halved after every filtering and down sampling operation. A wavelet transform is applied on output of high pass filter (approximation coefficients) recursively keeping the output coefficients of each low pass filtering operation (detailed coefficients) at each stage. The wavelet transform of a data at any level *n* of decomposition consists of approximation coefficients only at n^{th} level and all detailed coefficients up to n^{th} level. More details about the wavelet could be referred at Li T et al[16], Mallat[17] and Daubechies[18].

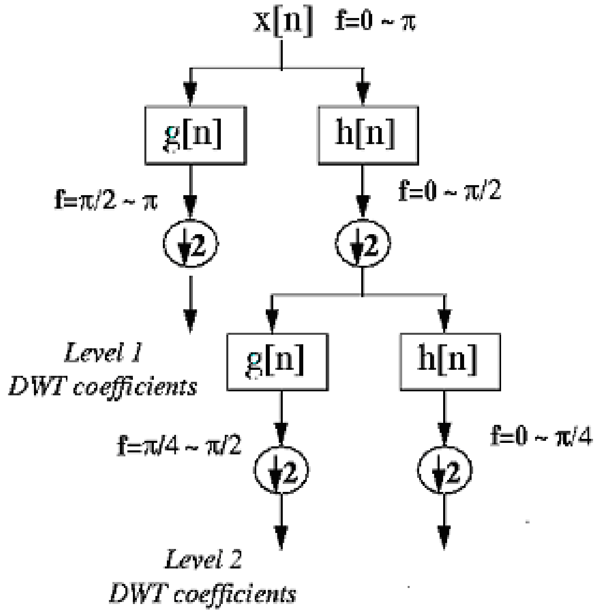

Figure 1: A Two Level DWT for N Data.

Methodology

The proposed image restoration technique in this paper is based on discrete wavelet transform. The wavelet transform was performed using haar. To test the effectiveness of the proposed method, non blind deblurring approach in which the blurring operator is a known PSF is worked out. The image under test is simulated with a blur and the proposed deblurring algorithm is administered to improve the downgraded image and compared with the original image using PSNR. The proposed method could be summarized as follows:

- Step 1: Read the blurred Image and convert into gray scale.
- Step 2: Find DWT of the input image
- Step 3: Calculate the components of wavelet energy i.e., approximation, detail, horizontal and vertical components.
- Step 4: Calculate the average of all the detailed coefficients
- Step 5: Add the average value calculated in step 4 with each and every value of the detail coefficient matrix.
- Step 6: The image is reconstructed with the updated detailed coefficients and other unaltered coefficients and checked for quality.
- Step 7: The steps from 1 to 6 could be repeated till getting an image with improved quality.
- Step 8: Calculate the MSE and PSNR values between the two images (i.e) blurred and the original image.

Results and analysis

The proposed approach for image deblurring based on haar wavelet transform was administered on three bench mark images namely, cameraman, lena, baby and fan.

These images were blurred with three types of noises namely average, Gaussian and disk. It is observed that the processed image using the proposed deblurring algorithm improved in quality. It could be observed both qualitatively and quantitatively. For quantitative measurements the usual PSNR values were used. For qualitative analysis visual observation could be used. The quantitative analysis is summarized in Table1.

Table1: PSNR values for various images with different types of noises

Name of the Image	Noise	PSNR between original and blurred image	PSNR between original and processed image
Camera man	Average	25.9114	80.4120
	Gaussian	34.5884	75.3065
	Disk	24.8560	70.9862
Baby	Average	33.8712	70.7667
	Gaussian	43.5050	66.4603
	Disk	32.8457	74.8232
Lena	Average	28.7886	67.2178
	Gaussian	37.3862	58.3706
	Disk	27.3456	70.5508
Fan	Average	30.4003	63.7109
	Gaussian	28.7840	60.5169
	Disk	39.1939	60.6230

The sample results for each noise for qualitative observation are presented in Figure 3 to Figure 5.

(a) (b) (c)

Fig.2:(a) Cameraman Original Image, (b) Cameraman Blurred Image With average Noise, (c) Deblurred Image

(a) (b) (c)

Figure 3: (a) Lena Original Image, (b)Lena Blurred Image With Gaussian Noise, (c)Deblurred Image

(a) (b) (c)

Fig 4: (a) Baby Original Image, (b) Baby Blurred Image With Disk Noise, (c) Deblurred Image

(a) (b) (c)

Fig 5: (a)Fan Original Image,(b)Fan Blurred Image with disk Noise,(c)Deblurred Image

It could be observed from the figures 2 to 5 that the blurred images were improved by quality after having administered with the proposed algorithm and the corresponding deblurred images could be observed to be visually better.

Conclusion

Image deblurring is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one. For deblurring the images a variety of techniques are used. But, they involve complex computations and methods. In this paper, a new approach using wavelet transform has been presented for restoration of such blurred images. The method is very simple and effective. Both the qualitative and quantitative results reflect could be observed in terms of improved visual observation and improved PSNR values. This shows that, in addition to its simplicity and effectiveness the proposed algorithm performed better and could be tried for high end applications also.

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