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IMAGE DE-BLURRING USING WIENER DE-CONVOLUTION AND WAVELET FOR DIFFERENT BLURRING KERNEL

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ABSTRACT

Image de-convolution is an active research area of recovering a sharp image after blurring by a convolution. One of the problems in image de-convolution is how to preserve the texture structures while removing blur in presence of noise. Various methods have been used for such as gradient based methods, sparsity based methods, and nonlocal self-similarity methods. In this thesis, we have used the conventional non-blind method of Wiener de-convolution. Further Wavelet denoising has been used to improve the image quality without deteoriating the fine structure of images. The method has been applied for different PSF and different images to validate the results of the de-blurring.

KEYWORDS: Wavelet Transform (WT), Wiener etc.

INTRODUCTION

Image de-blurring at its basics is taking any image that is not sharply focused and processing it to make it more clear to the viewer. Restoring an image that is "blurred" is one of the most highly publicized parts of image processing. There are several different kinds of image distortions that occur when you take a picture: noise, incorrect focusing, white balance error, exposure error, lens distortion, motion blur, and more. Most people would like their photos to come out sharp and focused, so that viewers can easily see what the photo is about. In our project we will focus mostly on incorrect focusing blur and motion blur. Most of the other distortions are well known and correctly, but the de-blurring of images that are focused incorrectly or have camera movement is still very much in development. We will mostly explore incorrect focus and various techniques currently available to de-blur images.

The below function outlines the concept of image de-blurring:

$$g(x, y) = h(x, y) * f(x, y) + n(x, y)$$

In this formula f(x,y) represents the un-blurred image coming to the camera CCD, h(x,y) represents the blur kernel, and n(x,y) represents the noise added due to the CCD. Notice that the noise is not convolved with the blur kernel, this is because the noise originates from the random motion of electrons in the camera's CCD array, which cannot be avoided and is not blurred. The noise is additive and Gaussian distributed which means that we don't have to worry about its correlation with the proper image itself (though definitely still have to deal with it!).

The blur kernel, also called the point spread function, is caused by improper focusing or by moving the camera while the image is being taken. You can imagine with motion blur that the pixels in the CCD array have smeared values for what is coming through the lens. There is now one point that has been smeared across multiple pixels. So for each pixel in the CCD we have the sum of multiple pixels in the nearby vicinity. We represent this blur using the point spread function. The advantage of writing the blur in this way is that we can artificially introduce blur by creating our own point spread function (PSF). This allows us to test the effectiveness of different de-blurring methods when we know exactly how the image was blurred.

The easiest and most obvious way to fix image blur is to look at this formula in the frequency domain (by doing the DFT):

$$G(\omega_1, \omega_2) = H(\omega_1, \omega_2) \times F(\omega_1, \omega_2) + N(\omega_1, \omega_2)$$

Then by dividing out by H(w1,w2), we get:

$$\frac{G(\omega_1,\omega_2)}{H(\omega_1,\omega_2)} = F(\omega_1, \omega_2) + \frac{N(\omega_1,\omega_2)}{H(\omega_1,\omega_2)}$$

That's great because now we have a solution for f(x,y) after doing the inverse DFT...except for one problem. The noise. Normally the human eye cannot detect the amounts of noise that the camera adds, but if H(w1,w2) has low values in any regions then the noise dominates in this formula and all hope of image recovery is lost.

Weiner de-convolution

The Wiener filter is an important tool in image processing and it essentially performs de-convolution. The formula for the Wiener filter reduces to:

$$G(\omega_1, \omega_2) = \frac{F(\omega_1,\omega_2)}{H(\omega_1,\omega_2)} \times \frac{|H(\omega_1,\omega_2)|^2}{|H(\omega_1,\omega_2)|^2 + \frac{1}{SNR(\omega_1,\omega_2)}}$$

Where G(w1,w2) is the deblurred image, F(w1,w2) is the blurred image, H(w1,w2) is the blur kernel, and SNR(w1,w2) is the signal-to-noise ratio. If there is no noise then the equation reduces to:

$$G(\omega_1, \omega_2) = \frac{F(\omega_1,\omega_2)}{H(\omega_1,\omega_2)}$$

This is exactly what we did in the basics of image de-blurring. But there are some cons of using the Wiener filter. In the representations of the images below we used de-convwnr function in MATLAB. It is noted that this function cannot recover the image perfectly, even when the noise is known. In fact, the original image can only be recovered perfectly when there is no noise and the point spread function is known. Noise has a huge impact on the quality of the recovered photo.

RELATED WORK

Hang Yang, Ming Zhu [1], propose an active research topic of recovering a sharp image given a blurry one generated by a convolution. One of the most challenging problems in image deconvolution is how to preserve the fine scale texture structures while removing blur and noise. The proposed hybrid algorithm is easy to implement and experimental results show that the proposed algorithm outperforms many state-of-the-art deconvolution algorithms in terms of both quantitative measure and visual perception quality. Rolling guidance filter has been proved to remove small-scale structures while preserving other content, parallel in terms of importance to previous edge-preserving filter, but it cannot preserve low-contrast detail like textures. short-time Fourier transform (STFT) shrinkage on the other hand results in good detail preservation, but it suffers from ringing artifacts near steep edges. Through twenty-four standard simulation experiments, it outperforms five existing state-of-the-art deconvolution algorithms.

Ramesh Neelamani [2], I this paper, propose an efficient, hybrid Fourier-wavelet regularized deconvolution (ForWaRD) algorithm that performs noise regularization via scalar shrinkage in both the Fourier and wavelet domains. The Fourier shrinkage exploits the Fourier transform's economical representation of the colored noise inherent in deconvolution, whereas the wavelet shrinkage exploits the wavelet domain's economical representation of piecewise smooth signals and images ForWaRD is applicable to all ill-conditioned deconvolution problems, unlike the purely wavelet-based wavelet-vaguelette deconvolution (WVD); moreover, its estimate features minimal ringing, unlike the purely Fourier-based Wiener deconvolution.

WAVELET DE-NOISING

To overcome obstacles of signal processing (including noise reduction in image processing), a method called the wavelet transform has been developed. In the case of image processing the wavelet transform is superior to the DFT (Discrete Fourier Transform) and the STFT (Short-Time Fourier Transform). The DFT cannot provide information about how the frequencies vary over time. The STFT solves this issue by taking windows of specified length and shifting them across the signal. This creates multiple DFT's of each of these windows and assumes that the signals in theses intervals are approximately time-invariant. There is still an issue with the STFT as one need to specify a window of a specific length and use it for the duration of the signal. Signals with a varying range of frequencies can be hard to evaluate because of this. Transients as a result of improper windows can cause aliasing and distort the evaluated signal. Wavelets address the issues of fixed window sizes of the STFT. Wavelets allow variable window sizes while analyzing different frequencies. This is possible by scaling a shifting a certain wavelet function. Small scales are used for high frequencies while large scales are used for low frequencies. Noise is unavoidable and almost unpredictable in the collection of images. Noise is exaggerated by the addition of Gaussian white noise to an out of focus image captured by a camera. Noise negatively affects the deblurring of the image. Using the Wavelet Toolbox in MATLAB, the noise is able to be removed. This allowed for a better deblurred image.

Symlets wavelet: - They are the modified version of daubechies wavelet increased in symmetry. It is also known as the least symmetry .It is defined by positive integer N. The scale function and wavelet function has the compact support length 2N. N is the vanishing moments.

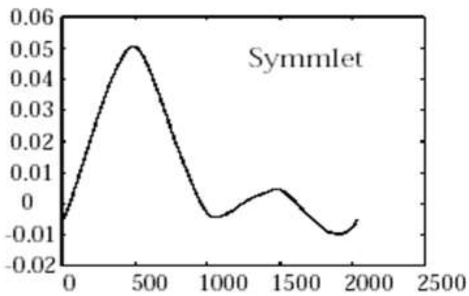

Fig 1. Symlets wavelet transforms

SYSTEM DESCRIPTION

The wavelet and wiener based image deblurring has been used in the proposed method the block diagram of simulation system is shown in figure:2.

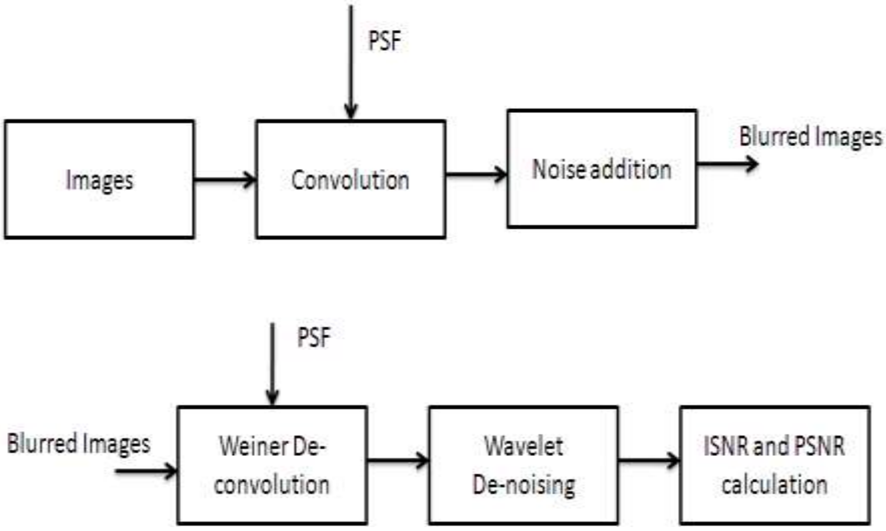

Fig 2. Block Diagram

RESULTS AND DISCUSSION

The simulation is done on the MATLAB version R2010b. Image de-convolution is an active research area of recovering a sharp image after blurring by a convolution. In this section we give the simulation of wavelet denoising in Wiener filter. We have found that the ISNR values generally reach the peak value when σ is 7 in iteration 4. We found that a large value of it would result in a smooth image whereas a too small value would lead to inadequate denoising.

Fig 3. Image deblurring on gray image Cameraman (256×256) with Wavelet and Wiener

Fig 4. Image deblurring on gray image House (256×256) with Wavelet and Wiener

Table 1. CAMERAMAN (256X256)

SCENARIO	1	2	3	4	5	6
METHOD						
ForWaRd	6.76	5.08	7.4	2.4	3.14	3.92
FTVd	7.41	5.24	8.56	2.57	3.36	1.37
L0-Abs	7.7	5.55	9.1	2.93	3.49	1.77
SURE-LET	7.54	5.22	7.84	2.67	3.27	2.45
PIEIAS	8.1	6.14	9.23	3.41	3.49	4.65
BM3DDED	8.19	6.4	8.34	3.34	3.73	4.7
DUAL DOMAIN	8.26	6.29	9.42	3.57	3.78	4.61
PROPOSED	3.457	5.6765	2.2112	6.4917	5.389	6.0985

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Table 2. HOUSE(256X256)

SCENARIO	1	2	3	4	5	6
METHOD						
ForWaRd	7.35	6.03	9.56	3.19	3.85	5.52
FTVd	7.98	6.57	10.39	4.49	4.72	2.44
L0-Abs	8.4	7.12	11.06	4.55	4.8	2.15
SURE-LET	8.71	6.9	10.72	4.35	4.26	4.38
PIEIAS	8.94	7.76	11.22	4.85	4.94	7.07
BM3DDED	9.32	8.14	10.85	5.13	4.56	7.21
DUAL DOMAIN	9.48	8.3	12.17	5.32	5.2	6.94
PROPOSED	4.9454	6.3956	3.0952	5.7764	6.8912	5.8507

CONCLUSION

The method of the Wiener and Wavelet has been applied for different cases of blurring with noises. The ISNR value has significantly improved by this method for 4th PSF the result is higher than the work done by the author Hang Yang. There is an open area to use the different wavelet other than sym4 which is used in this method.

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