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EXTERMINATION OF BLURRING CAUSED BY MOTION IN IMAGES USING ITERATIVE BLIND DE-CONVOLUTION APPROACH

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ABSTRACT: Currently Blurring and its extermination techniques in the presence of noise have become a most attentive area of digital image processing under image restoration. There exist several approaches and techniques for image de-noising that include linear filters, non linear filters and Fourier /wavelet transforms. Image restoration is a well defined efficient step that proposes or suggests to reform or recover an image which has been degraded by blurring sources i.e. camera shake, motion of object, motion of subject, height of field, movement of snap or image, movement of scene etc.

Image restoration which is considered as direct approach as results are generated in one iteration step fashion, actually works like indirect approach in which restoration final results are achieved after a number of steps or iterations. The difficulty arise for our above two approaches is that, in both approaches the details associated with the Blurring functions, complete knowledge details about blurring function like Point Spread Function (PSF), estimation of power spectrum whose availability is not subjected directly or indirectly with the study of blurring parameters & deals with image processing functionality under blurring.

In this paper we discuss a very efficient and effective iteration based approach in frequency domain using Blind De-convolution approach that performed iteratively where by each iteration is starts with the improvement of the estimation of point spread function and the scene that results a very efficient recovered sharp version of the blurred image.

Keywords: Iteration based De-convolution approach, Frequency Domain, Point Spread Function (PSF), Image Restoration.

1. INTRODUCTION

Blurring is the most powerful operation that is used in image processing areas that mainly focuses on pixels in the source image for each & every pixel that is a well defined and most considered part of the resulting image that was being blurred.

Blurring significantly degrade the visual quality of photographs, captured images as it is the well known form of reduction of the image bandwidth that is caused due to improper and imperfect formation and production of image.

Blurring is caused by the relative motion between the imaging system like camera and the captured image means the actual scene or snap for which that image is captured, in the mean time interval of integration time interval of image.

Normally noise and low pass masks degrades the quality of image and also these masks are used to blur/smooth the snap or image using certain formulas, analysis and functions.

Blurring effects are easily and clearly seen in the snaps that are taken with distant and long focuses and exposures of intervals of time and the snaps or object imaging system with the movement in a slow or rapidly motion.

The extermination of blurring caused by motion (motion de-blurring) specially contains two very important challenges on which it completely and conceptually depends:

(*i*) Estimating blur kernels, or point-spread functions (PSF), from blurred images.

(*ii*) Extermination of the blurring from the images to obtain a recovered blur-free image.

Normally, an image can be degraded using low-pass filters and its noise. This low-pass filter is used to blur/smooth the image using certain functions. In digital image there are three common types of Blur effects: Average Blur, Gaussian Blur and Motion Blur. Image deblurring can performed for better looking image, improved identification, PSF calibration, higher resolution and better quantitative Analysis.

1.1. Model of Deblurring Approach

A blurred or degraded image can be approximately described by this equation $g = H*f + n$, where:

g = The blurred image, H = The distortion operator, also called the point spread function (PSF). This function, when convolved with the image, creates the distortion. f = The

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original true image, n = Additive noise, introduced during image acquisition, that corrupts the image introduced during image acquisition, that corrupts the image[1]. Image deblurring is an inverse problem which is used to recover an image which has suffered from linear degradation. The blurring degradation can be space-invariant or space-in variant [4]. Image deblurring methods can be divided into two classes: nonblind, in which the blurring operator is known and blind, in which the blurring operator is unknown.

1.2. Filtering Technique: An Image Can be Restored Using Two Basic Approaches. They Are:

1.2.1. Inverse Filtering

Inverse filter restores a blurred image perfectly from an output of a noiseless linear system. However, since the inverse filter is a form of high pass filer, in the presence of additive white noise, it does not work well. If we know of or can create a good model of the blurring function that corrupted an image, the quickest and easiest way to restore that is by inverse filtering. We can model a blurred image by

$$g(n_1, n_2) = f(n_1, n_2) ** b(n_1, n_2) \tag{1}$$

Where f is the original image, b is some kind of a low pass filter and g is our blurred image. So to get back the original image, we would just have to convolve our blurred function with some kind of a high pass filter

$$f(n_1, n_2) = g(n_1, n_2) ** h(n_1, n_2) \tag{2}$$

We can find h, if we take the DFT of b.

1.2.2. Weiner Filtering

The Wiener filter isolates lines in a noisy image by finding an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image. 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 [2] can be expressed as follows:

$$W(f1, f2) = \frac{H^*(f1, f2) S_{xx}(f1, f2)}{|H(f1, f2)|^2 S_{xx}(f1, f2) + S_{\eta\eta}(f1, f2)} \tag{3}$$

Where $Sxx(f1, f2)$, $S_{\eta\eta}(f1, f2)$ power spectra of the original image and additive are noise respectively, and $H(f1, f2)$ is the blurring filter. It is easy to see that the Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. It not only performs the deconvolution by inverse filtering (high-pass filtering) but also removes the noise with a compression operation (low-pass filtering).

The problem with this method is that they require knowledge of the blur function that is point spread function (PSF) and estimation of power spectrum.

2. RELATED WORK

The major difficulty of motion deblurring is accurate estimation of motion blur kernels, in other words, motion point spread functions (PSFs). Most prior approaches ex-tensively focus on a single motion PSF caused by a camera, but not spatially-varying motion PSFs caused by multiple objects' motions. Yitzhakey et al. propose a method for motion deblurring by identifying the motion PSF using an isotropic image assumption [5]. Assuming an 1D directional motion blur in their model, they extract the motion component from the image in the frequency domain using autocorrelation. Afterwards, they extend their method to account for a high frequency motion blur caused by vibration that is observed along with the major 1D directional motion blur [6]. Recently, Jia proposes a deblurring method that uses the translucency information of blurry regions between two opaque regions [7]. The information is acquired by image matting and used to estimate a single motion PSF. In the multiple image framework, Chen et al. propose a method for recovering the original image from two consecutively blurred images [8]. The method adopts an energy minimization technique that computes the best translation of the camera from the two consecutive images. Similarly, Rav-Acha and Peleg [9] use two blurry images (one is horizontally and the other is vertically blurred) for deblurring by simultaneously estimating parameters of image displacements using iterative energy minimization. Bascle et al. propose a method to remove motion blur and generate high-resolution images from an image sequence by finding pixel wise motion [10]. Bar et al. developed a unified framework of segmentation and blind restoration by treating the image segmentation and restoration as a coupled problem [11]. While they use a classical colour-based image segmentation without using the motion blur kernel for the segmentation, convincing results are obtained with the proposed method. Yuan et al. use a blurred/noisy image pair to handle uniform motion blur [12]. They also propose a novel deconvolution method that reduces ringing artifacts. Recently, a few works for removing spatially-variant motion blur have been proposed. Levin proposes a method to restore a blurry image that contains one motion blurred object and a sharp background [13]. The algorithm uses the statistical distributions of image gradient to estimate motion blurs and to locate a blurry foreground object. Bards-ley et al. use a phase diversity method to find motion PSFs in which segmentation is performed by splitting an image into regions that have homogeneous motion PSFs [14].Apart from these post-processing approaches, a few hardware approaches have been proposed as well. Ben-Ezraand Nayar develop a hybrid imaging system [15] that consists of two cameras: one is high-resolution with a long exposure time, the other is low resolution but can capture multiple frames with a shorter exposure time. Using the low-resolution camera for estimating the camera motion, their method estimates PSF for the high resolution camera. It is known that hardware approaches can handle more general camera motions than software approaches. However, such hardware systems are still expensive, and unfortunately they are not commonly available.

3. PROPOSED ALGORITHM FOR EXTERMINATION OF BLURRING CAUSED BY MOTION IN IMAGES

The method proposed in this paper reduces the noise in the image restored by Iterative Blind De-convolution approach with different blur parameters like length and blur angle. Proposed algorithm is to reconstruct frequency components. like edges which have been degraded by noise Results are evaluated and compared based on Evaluation Metrics Mean Square Error [MSE] and Signal-to-Noise Ratio [SNR]. Fig.1 shows a block diagram of our method.

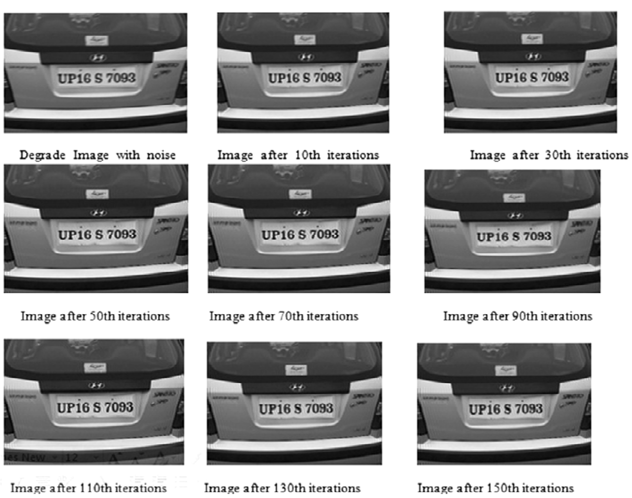

Figure 1: Results of the Proposed Algorithm for Image Deblur

3.1. Benefit of Iterative Blind De-Convolution Approach

Using this approach we easily identifying linear motion blur to compute the two-dimensional function of the blurred image $g(x, y)$ that is given by

$$B\,(g(x, y)) = F-1\ (\log |F\,(g(x, y))|) \qquad (4)$$

3.2. Blurring Parameter

The parameters needed for blurring an image are PSF, Blur length, Blur angle and type of noise. Point Spread Function is a blurring function. When the intensity of the observed point image is spread over several pixels, this is known as PSF. Blur length is the number of pixels by which the image is degraded. It is number of pixel position is shifted from original position. Blur angle is an angle at which the image is degraded. Available types of noise are Gaussian noise, salt and pepper noise, Poisson noise, Speckle noise which is used for blurring. In this paper, we are using Gaussian noise which is also known as white noise. It requires mean and variance as parameters.

3.3. Steps of Image Degradation and Extermination of Motion Blur

First the original image is degraded or blurred using degradation model to produce the blurred image. The blurred image should be an input to the deblurring algorithm. Various algorithms are available for deblurring. In this paper, we are going to use our proposed algorithm. The result of this algorithm produces the deblurring image which can be compared with our original image.

4. PROPOSED ALGORITHM

Proposed Algorithm can be used effectively when no information of distortion is known; it restores image and PSF

Steps:

Step 1: First assume that $\tilde{f}_o$ use a positive constant image with a constant value equal to average of the blurred image.

Step 2: This step of the iteration performs a convolution of the current assumption with the

$$\text{PSF:}\ \square\, n = \otimes\, h\ \tilde{}fn$$

Step 3: In this step compute a correction factor based on the result of the last operation and the original (degraded) image simultaneously. Instead of computing the desired (deblurred) image directly, our method computes a sequence of images, which converges to the desired image. Our algorithm is based on the following:

$$\O\, n = \tilde{}h \otimes g/\square n$$

Where "$g/\square\, n$" denotes pixel by pixel division. Assume, if some pixel values of $\square\, n = 0$, then we get

$$g/\square\, n = 0.$$

Step 4: At this step, a new assumption is the product of the current one and the correction factor

$$\tilde{}fn + 1 = \tilde{f}_n\,.\,\O n$$

Where "." is the pixel by pixel multiplication.

Step 5: At the final step, we get the restored image of image $g(x, y)$ by our proposed algorithm.

$$g(x, y) = \tilde{f}_{n+1} - 1 \ (\log |\tilde{f}_{n+1} \ (f(x, y))|)$$

Where $f(x, y)$ is the degraded image and $g(x, y)$ is the restored image after applying proposed algorithm.

5. SAMPLE RESULTS

The below images represent the result of proposed algorithm. The sample image after applying the proposed algorithm will be as follows:

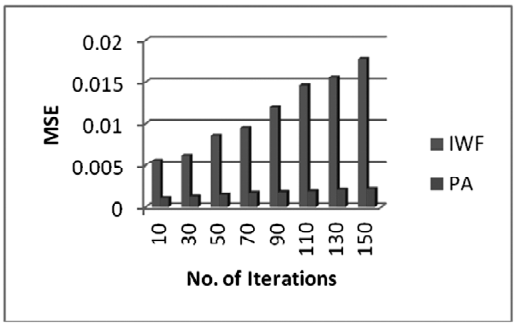

Figure 2: Graph of MSE for Comparison of Iterative Wiener Filter (IWF) and Proposed Algorithm (PA)

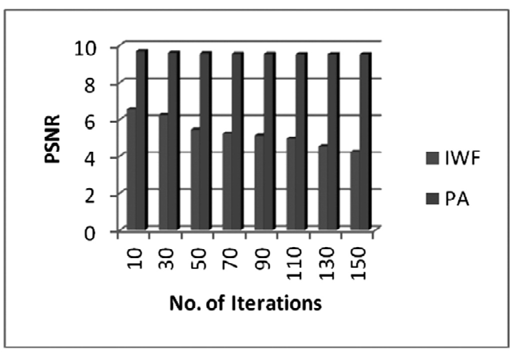

Figure 3: Graph of PSNR for Comparison of Iterative Wiener Filter (IWF) and Proposed Algorithm (PA)

Table 1
MSE Performance Measure Values for values for IWF and Proposed Algorithm

No. of Iterations	*IWF*	*PA*
10	0.0056	0.0011
30	0.0062	0.0013
50	0.0086	0.0015
70	0.0095	0.0017
90	0.012	0.0018
110	0.0146	0.0019
130	0.0156	0.0021
150	0.0178	0.0022

Table 2
PSNR Performance Measure Values for Values for IWF and Proposed Algorithm

No. of Iterations	*IWF*	*PA*
10	6.542	9.6828
30	6.234	9.592
50	5.425	9.5631
70	5.236	9.5398
90	5.123	9.5351
110	4.956	9.5238
130	4.526	9.5184
150	4.226	9.515

6. CONCLUSION

We have presented a method for Iterative blind image deblurring. The method differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges. The restoration quality of our method was visually and quantitatively better than those of the other algorithms. The advantage of our proposed algorithm is used to deblur the degraded image without prior knowledge of PSF and estimation of power spectrum.

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REFERENCES

[1] Jing Liu, Yan Wu "Image Restoration using Iterative Wiener Filter", *ECE533 Digital Image Processing Course Project*, December 13.

[2] Furuya, Eda, and T. Shimamura "Image Restoration via Wiener Filtering in the \Frequency Domain" *Wseas Transactions on Signal Processing* Issue 2, **5,** pp. 63-73 February 2009.

[3] Salem Saleh Al-amri et.al. "A Comparative Study for Deblured Average Blurred Images", Journal **02,** No. 03, 2010, pp. 731-733.

[4] Michal Sorel and Jan Flusser, Senior Member, "IEEE., Space-Variant Restoration of Images Degraded by Camera Motion Blur", *IEEE Transaction on Image Processing*, **17,** pp. 105-116, No. 2 Febreary 2008.

[5] Y. Yitzhaky, I. Mor, A. Lantzman, and N.S. Kopeika, "Directmethod for Restoration of Motion-Blurred Images," *Journal of Opt. Soc. Am. A.*, 15, No. 6, pp. 1512-1519, 1998.

[6] Y. Yitzhaky, G. Boshusha, Y. Levi, and N. S. Kopeika, "Restoration of an Image Degraded by Vibrations Using Only a Single Frame", *Optical Engineering*, **38,** No. 8, 2000.

[7] Jia, "Single Image Motion Deblurring Using Transparency," *in Proc. of Computer Vision and Pattern Recognition*, pp. 1-8, 2007.

[8] W.-G. Chen, N. Nandhakumar, and W. N. Martin, "Image Motion Estimation from Motion Smear - a New Computational Model", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, **18,** No. 4, pp. 412-425, 1996.

[9] A. Rav-Acha and S. Peleg, "Two Motion-Blurred Images are Better than One", *Pattern Recognition Letters*, **26,** pp. 311-317, 2005.

[10] B. Bascle, A. Blake, and A. Zisserman, "Motion Deblurring and Su-Perresolution from an Image Sequence," *in Proc. of European Con-Ference on Computer Vision*, **2,** pp. 573-582, 1996.

[11] L. Bar, N. Sochen, and N. Kiryati, "Variational Pairing of Image Seg-mentation and Blind Restoration", *in Proc. of European Conferenceon Computer Vision*, **2,** pp. 166-177, 2004.

[12] L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, "Image Deblurring with Blurred/Noisy Image Pairs", *ACM Trans. on Graphics* (*SIGGRAPH*), **26,** No. 3, pp. 1, 2007.

[13] A. Levin, "Blind Motion Deblurring Using Image Statistics," *in Advances in Neural Information Processing Systems*, 2006.

[14] J. Bardsley, S. Jefferies, J. Nagy, and R. Plemmons, "Blind Iterative Restoration of Images with Spatially Varying Blur," *Optics Express*, **14,** pp. 1767-1782, 2006.

[15] M. Ben-Ezra and S. K. Nayar, "Motion-Based Motion Deblurring", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, **26,** No. 6, pp. 689-698, 2004.

[16] Liu Ce, T. Freeman William, Szeliski Rick and Kang Bing Sing (2006). "Noise Estimation from a Single Image". *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), 2006, pp. 62.

[17] M´elange Tom, Nachtegael Mike, Kerre Etienne E. (2009). "A Fuzzy Filter for the Removal of Gaussian Noise in Color Image Sequences", pp. 1474-1479.

[18] Orlando.J, Tobias (2004). "Image Segmentation by Histogram Thresholding Using Fuzzy Sets". *IEEE Transaction on Image Processing*, **11,** No.12.

[19] Ozkan M. K., Sezan M. I. and Tekalp A. M (1993). "Adaptive Motion Compensated Filtering of Noisy Image Sequences". *IEEE Trans. CSVT*, **3,** pp. 277-289, 1993.

[20] Richardson Hadley William (1972). "Bayesian-Based Iterative Method of Image Restoration". *Journal of the Optical Society of America*, **62:** pp. 55-59.

[21] Shan Qi, Jia Jiaya Leo and Agarwala Aseem (2008). "High-Quality Motion Deblurring from a Single Image". *ACM Transactions on Graphics* (*Proc. of SIGGRAPH*), 2008. 14, 15, 30, 41, 42, 43, 45, 48, 51, 111, 114.

[22] Simmons Joseph, Topper Benjamin, Wolfson Avi. Fourier Filtering for Removing Motion Blur in Images, Modern Optics - Keto, 2007.

[23] Sorel Michal and Sroubek Filip (2009). "Space-Variant Deblurring using one Blurred and one Underexposed Image". *In Proceedings of the IEEE Conference on Image Processing* (*ICIP*), 2009,96.

[24] Sunghyun Cho, Yasuyuki Matsushita, and Seungyong Lee (2007). "Removing Non-Uniform Motion Blur from Images". *In Proceedings of International Conference on Computer Vision* (*ICCV*), 2007, pp 30, 96, 109, 111.

[25] Whyte Oliver, Sivic Josef, Zisserman Andrew and Ponce Jean (2010). "Non-Uniform Deblurring for Shaken Images". *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), 2010.

[26] Yuan Lu, Sun Jian, Quan Long, and Shum Yeung Heung (2007). "Image Deblurring with Blurred/Noisy Image Pairs". *ACM Transactions on Graphics* (*Proc. of SIGGRAPH*), 2007. 30, 96, 109, 111.