ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 8, August 2013

Comparative Analysis of Various Techniques for Non-Blind Restoration of Images

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Abstract: Image deblurring and restoration has been of great importance nowadays. Image recognition becomes difficult when it comes to blurred and poorly illuminated images and it is here image restoration come to picture. There have been many methods that were proposed in this regard and in this paper we will examine different methods and technologies discussed so far. The merits and demerits of different methods are discussed in this concern.

Keywords: PSF, SALSA, PDE, MMSE, PSNR

1. INTRODUCTION

Vision is the foremost trusted source of information compare to other human perceptions. And image is the basic container of any pictorial information. The process of retrieving and analyzing the pictorial information by a digital computer is known as digital image processing. The improvement of pictorial information for human interpretation and processing of scene data for autonomous machine perception. are the root application areas that had shown the interest in image processing field decades ago[1] Image deblurring is usually the first process that is used in the analysis of digital images. In any image denoising technique it is very important that the denoising process should not have any blurring effect on the image, and makes no changes on the preserving of images to image edges. There are several methods for image denoising; these are averaging filters, mean filters, and median filters [2] which are used in digital image processing for such purposes. But these filters have adverse effects on the sharp edges which make softening of the image and provide better smoothing the image. The softening of sharp images can be overcome using the partial differential equations (PDEs) –based methods and SALSA which have been introduced in the literature [3,4]. The partial differential equation is used to describe the implementation details of the Horizontal deblurring algorithm, Vertical deblurring algorithm, combination of both algorithms and SALSA (Split Augmented Lagrangian Shrinkage Algorithm). The relative motion of camera in vertical direction and the joint effect of the motion in two directions by introducing blur component in horizontal and vertical directions. SALSA can be used with different types of regularization, is based on a variable splitting technique which yields an equivalent constrained problem. The paper is organized as follows: Section 2 briefly describes the different techniques used for image deblurring with PDE-based approaches and SALSA technique for image denoising. Section 3 introduces parameters used for performance measuring algorithms in this paper. The experimental results are provided in Section 4. Finally, the conclusion is given in Section 5

2. LITERATURE REVIEW

The median filtering, mean filtering and other image denoising techniques are used for the better smoothing the image but PDE and SALSA have proven a significant improvement over these techniques. In this section we introduce the different techniques of image deblurring

2.1 Weiner Filter

The method is founded on considering image and noise as random process and objective is to find an estimate of deblurred image of the uncorrupted image such that mean square error between them is minimized. The simplest approach is to restore the original image simple by dividing the transform of degraded image by degradation function.

$$F'(u,v)=F(u,v)+N(u,v)/H(u,v) \quad (1)$$

These are the frequency transform of deblurred image, original image, noise density and degraded function

2.2 Order Statistics Filters

These are the spatial filters whose response is based on the ordering of the pixels contained in the image area and compassed by the filter. The response of the filter at any point is determined by ranking result.

$$F1(x,y)=median\{g(s,t)\} \quad (2)$$
$$F1(x,y)=max\{g(s,t)\} \quad (3)$$
$$F1(x,y)=mean\{g(s,t)\} \quad (4)$$

2.3 PDE Deblurring

A generalized PDE [5] based image model is proposed to model the phenomenon of blurred image formation due to relative motion between camera and the object and further the recovery of original image in spatial domain. Lax scheme is used to

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ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
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discretize the resulting PDE which is mathematically stable and produces good result. Therefore, with the use of Lax method for discretizing the proposed PDE that was initially a flux conservative equation transforms to a ID flux conservative equation with an added diffusion term which is in the form of Navier-Stokes equation. The, additional diffusion term contributes towards further smoothing of image.Let vector $\underline{X} \in R^n$, $f : R^n \to R$ and $\underline{X} = (x_1, x_2, \ldots, x_n)$ and f is a function of $\underline{X}$. For 1D object $f(\underline{X}) = x$ and for 2D object i.e. images $f(\underline{X}) = (x, y)$. Let $\underline{V}$ represents the velocity vector of object and $\underline{V} = (v_1, v_2, \ldots, v_n)$.If object is moving in horizontal direction only then velocity reads as $\underline{V} = v_x$ and if object is under motion in XY-space in both horizontal and vertical directions then velocity vector reads as $\underline{V} = (v_x, v_y)$. If n-dimensional object $f(\underline{X})$ keeps a linear uniform motion at a rate $\underline{V}$ in n-Dim space under the surveillance of a camera. The total exposure $g(\underline{x}, t)$ at any point of the recording medium(e.g., film) is obtained by integrating the instantaneous exposure over the time interval 0<=t<=T during which camera shutter is open. After discretization using Navier-Strokes equation, we get Observed object for duration T can be modeled as

$$g(\underline{X}, t) = \int_0^T f(\underline{X} - \underline{V}t)\,dt \qquad (6)$$

$$g_j^{n+1} = g_j^n - (v\Delta t)\frac{\partial g}{\partial x} + \frac{(\Delta x)^2}{2}\frac{\partial^2 g}{\partial x^2} \qquad (7)$$

From above derived equation the PDE equation is

$$It = It - (v\Delta t)\frac{\partial g}{\partial x} + \frac{(\Delta x)^2}{2}\frac{\partial^2 g}{\partial x^2} \qquad (8)$$

2.4 SALSA

The SALSA [5,6] is based on the technique known as variable splitting. Since the objective function to be minimized is the sum of two functions, the idea is to split the variable x into a pair of variables, say x and v, each to serve as the argument of each of the two functions, and then minimize the sum of the two functions under the constraint that the two variables have to be equal, so that the problems are equivalent. Although variable splitting is also the rationale behind the recently proposed split-Bregman method.The constrained optimization problem resulting from variable splitting is then dealt with using an Augmented Lagrangian (AL) scheme, which is known to be equivalent to the Bragman iterative methods recently proposed to handle imaging inverse problems. The term SALSA (split augmented Lagrangian shrinkage algorithm), comes from the fact that it uses (a regularized version of) the Hessian of the data fidelity term of, that is, AH A, while the above mentioned algorithms essentially only use gradient information Consider an unconstrained optimization problem in which the objective function is the sum of two functions, one of which is written as the composition of two functions

$$\min_{u \in R^n} f_1(u) + f_2(g(u)) \qquad (9)$$

Where $g : R^n \to R^d$.Variable splitting is a very simple procedure that consists in creating a new variable, say v, to serve as the argument of f_2, under the constraint that g(u) = v. This leads to the constrained problem

$$\min_{u \in R^n, v \in R^d} f_1(u) + f_2(v) \qquad (10)$$

Subject to g(u)=v,which is clearly equivalent to unconstrained problem The constrained problem is attacked by a quadratic penalty approach, i.e., by solving

$$\min_{u \in R^n, v \in R^d} f_1(u) + f_2(v) + \frac{\alpha}{2}\|g(u) - v\|_2^2 \qquad (11)$$

by alternating minimization with respect to u and v, while slowly taking α to very large values (a continuation process).And the ALM(Augmented Langrangian method) is defined as

$$L_A(z, \lambda, u) = E(z) + \lambda^T(b - Hz) + \frac{u}{2}\|Az - b\|_2^2 \qquad (12)$$

Where $\lambda \in R^P$ is a vector of Lagrange multipliers and u ≥ 0 is called the penalty parameter.

3. PERFORMANCES PARAMETERS

In this section we discuss the two performance measuring parameters on which the above discussed techniques are compared.

3.1 MMSE(Minimum mean square error)

In statistics and signal processing first error metrics, a minimum mean square error (MMSE) estimator is an estimation method which minimizes the mean square error (MSE) of the fitted values of a dependent variable, which is a common measure of estimator quality. Let x be a n*1 unknown (hidden) random vector variable, and let y be a m*1 known random vector variable (the measurement or observation), both of them not necessarily of the same dimension. An estimator $\hat{x}(y)$ of x is any function of the measurement y. The estimation error vector is given by $e = \hat{x} - x$ and its mean squared error (MSE) [6] is given by the trace of error covariance matrix

$$MSE = tr[E\{(\hat{x} - x)(\hat{x} - x)^T\}] \qquad (13)$$

Where the expectation is taken over both x and y. When x s a scalar variable, then MSE expression simplifies to $E\{(\hat{x} - x)^2\}$.Note that MSE could equivalently be defined in other ways, since

$$tr\{E(ee^T)\} = E\{tr(ee^T)\} = E\{e^T e\} = \sum_{i=1}^n E\{e_i^2\} \qquad (14)$$

The MMSE estimator is then defined as the estimator achieving minimal MSE.

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International Journal of Advanced Research in Computer and Communication Engineering
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3.2 PSNR(Peak Signal to Noise Ratio)

Second of the error metrics used to compare the various image deblurring technique is the (Mean Square Error and PSNR) Peak Signal to Noise Ratio (PSNR) [7]. The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{X=1}^{N}[I(x,y)-I^{'}(x,y)]^{2} \qquad (15)$$

PSNR = 20 * log10 (255 / sqrt(MSE)) (16)

Where I(x, y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a lower MSE (and a high PSNR), you can recognize that it is a better one.

4. EXPERIMENTAL RESULTS

To compare the performance of the above described techniques in image denoising, they have been implemented using Matlab. Then the algorithms were applied to standard Cameramen image. In these experiments, to make the images noisy, the Gaussian noise has been used with 64 as the average value for both of the noises, and a variance of 400 for the Gaussian noise, respectively. These noises have been added to the images.

4.1 Results for Image deblurring using SALSA

Figure. 1: original Image

Figure 2: Blurred and noisy image

Figure3: Estimated image using SALSA

4.2 Results for Image deblurring using PDE

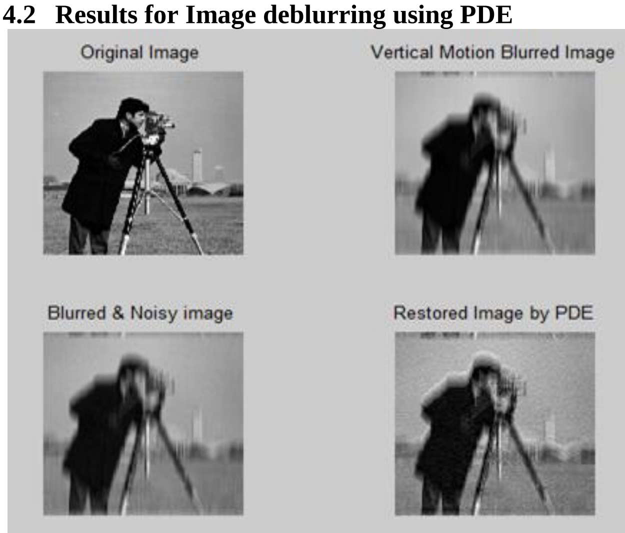

Figure4 Image Deblurring using PDE

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ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 8, August 2013

4.3 Results for image deblurring using Wiener filter

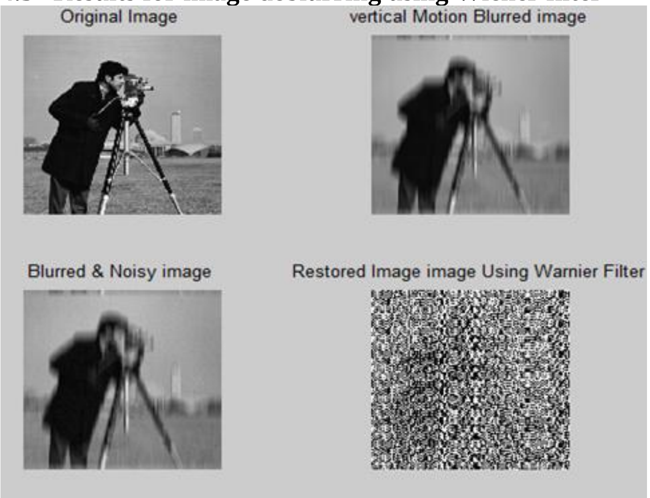

Figure 5: Image Deblurring using Wiener filter

4.4 Results for image deblurring using Median filter

Figure 6 Image Deblurring using Median filter

5. CONCLUSION

In this research various methods for noise reduction have been analyzed. In the analysis, various well-known measuring metrics have been used. The results show that by using the SALSA noise reduction is much better compared to other methods. In addition, by using this method the quality of the image is better enhanced. Using SALSA the unconstrained image problem can be easily done regularized. The median, mean and wiener filters have low PSNR values for Gaussian noise. Weiner filtering is the worst case for such noises. The PDE technique is much efficient than these for the motion blurring. The vertical deblurring shows the better results than horizontal and combined deblurring in PDE but still it is less efficient than the SALSA. The comparison table is shown in Table no.1

Table1.COMPARSION TABLE

Technique used	Type of noise	Performance	PSNR values
SALSA	Gaussian Noise	Very Efficient	40.001
PDE_ Vertical	Gaussian Noise	Efficient	38.8836
Weiner_Vertical	Gaussian Noise	Worst Results	11.1457
Median_Vertical	Gaussian Noise	Better	26.6929

6. ACKNOWLEDGMENT

Ablend of gratitude, pleasure and great satisfaction is what I feel to convey my indebtedness to all those who directly or indirectly contributed to the successful publication of this paper. I express my profound and sincere gratitude to my Guide, Mr.Puneet Sharma, A.P in CSE department, whose Persistence guidance and support helped me in the successful completion of the paper in stipulated time. His expert knowledge and scholarly suggestion help me a lot. I am grateful to Mr. Neeraj Gupta, HOD, CSE, HCE Sonepat for his support. I am thankful to all my Professors and Lecturers and members of the department for their generous help in various ways for the completion of this work.

REFERENCES

[1] A. C. Likas, N. P. Galatsanos. A Variational Approach for Bayesian Blind Image Deconvolution". IEEE Transactions on Signal Processing, Vol. 52, No. 8:2222,2233, 2004
[2] Gonzalez C.Rafeal,Woods Richard E., "DigitalImageProcessing", London:Pearson Education, 2002.
[3] Rajeev Srivastava, Harish Parthasarthy, JRP Gupta and D. Roy Choudhary, "Image Restoration from Motion Blurred Image using PDEs formalism", IEEE International Advance Computing Conference (IACC 2009),March 2009.
[4] M.D. Kostin, "Schrodinger-Fuerth quantum diffusion theory: Generalized complex diffusion equation", J. Math. Phys. 33 (I), 1992
[5] Manya V.Afonso, Jose M. Bioucas-Dias ,Mario A.T.Figueiredo, "Fast Image Recovery Using Variable Splitting and Constrained Optimization", IEEE Transactions on Image Processing,2010
[6] A. Chambolle "An algorithm for total variation minimization and applications," J. Math. Imaging Vis., vol. 20, no. 1-2, pp. 89–97, 2004.
[7] "Image Processing Science calculating RMSE and PSNR for color images". Retrieved 6 April 2011
[8] www.google.com