Deblurring using Reverse Filtering Techniques: An Experimental Analysis

Dr. Usha Rani

Associate Professor, Department of Computer Science, University College Ghanaur, Patiala

Abstract
Images are an integral part of life. Blurring an image is a process that makes the image less sharp and distorts the detail of an image. The images got blurred due to atmospheric noise, improper camera setting, and relative motion between the camera and the scene. Deblurring is the process of recovering the sharp image from the blurred image. The types of blurs include Average blur, Motion blur, Defocus blur, Gaussian blur, etc. Mainly deblurring techniques are categorised into blind image deconvolution and nonblind image deconvolution. There exist many deblurring techniques in the literature. Deblurring using reverse filtering is to suppress the effect of the filter using the filter itself as many times as needed but without knowing its internal structure. The filter is regarded as a black box. This paper presents the experimental analysis of existing reverse filtering techniques such as zero order reverse filtering (T-method), Rendition method (R-method), P-method, and TDA (Total Derivative Approximation). The methods considered in the paper are spatial domain methods.

Keywords: Reverse Filtering, Deblurring, Defiltering

1. Introduction

In the modern time we largely deal with the images. During acquisition these images get degraded due to many reasons. Blur refers to the degradation that decreases the overall sharpness of the image. Blur in introduced due to many reasons such as; improper setting of the camera, relative motion between the camera and the scene, out of focus, poor lens quality, and atmospheric noise etc. Blur in the image leads to reduction in aesthetic and integrity of the image. Blurry image is represented as the convolution of the image with associated point spread function along with additive noise as given below:

$J = I * p + n$ (1)

Where *'I'* is the original image, '*J*' is the blurred image, * is the convolution operator, *p* is the point spread function, and *n* is the additive noise introduced during image acquisition.

Deblurring is the process to recover sharp image from the blurred image. Generally, the blurred image contains insufficient information to uniquely determine the sharp original image, thereby making it a challenging job. Depending on the availability of blurring information, image deblurring techniques can be divided as blind and non-blind. In nonblind deblurring, prior information about the corresponding PSF and the additive noise is known. In contrast, in blind deconvolution, deblurring is attained without any prior knowledge regarding the PSF and the additive noise. Blind deconvolution approach is more suited for real world scenario because during capturing images are corrupted by unknown parameter which can be Gaussian noise, atmospheric turbulence, motion blur, etc. Multi-image deblurring uses multiple images of the same scene that are blurred differently to estimate the blur kernel and original image more

accurately. Inverse filtering, Wiener filtering, Richardson-Lucy algorithm, iterative methods, deep learning models, joint optimization, and fusion methods are all techniques used in image deblurring.
Image deblurring is often an iterative process. The deblurring process may have to be repeated multiple times to vary the parameters specified to the deblurring method with each iteration, until an image is achieved that is the closest approximation of the original image.

2. Reverse filtering

Reverse filtering is the process of recovering the original clean image (I) from the blurred image (J) without knowing the internal structure of the filter.
Generally filtering process can be expressed as
J=f(I) (2)
Where, I is the input clean image and J is the blurred image. After filtering J is still the function of I. Reverse filtering is an iterative process. We can apply the filtering process f(.) as many times as needed. In reverse filtering our aim is to estimate input image I from filtered image J without computing $f^{-1}(.)$. Filter f(.) is considered as black box.
Numerical methods such as Newton Rapson's methods and its variations, Gradient descent methods, and fixed-point iterations can be used to solve the equation (2). These methods need the Jacobian of f(.) to estimate the reverse of equation. It is not computationally feasible because the image consists of millions of pixels.
Reverse filtering to recover blurred images is firstly introduced by [1].

3. Reverse Filtering Techniques

3.1 T-method

The T-method [1] originally known as zero order reverse filter, is an iterative method having lowest programming complexity among all the reverse filtering techniques considered in this paper. This method updates the recovered image from previous iteration using the following equation:
$X^{t+1} = X^t + J - f(X^t)$ (3)
Here, J is the filtering result of the image I, i.e., J=f(I). We have to compute image I by reverse filtering the image J. Both I and f(.) are unknown. X^t is the estimate of I in t^{th} iteration. This method does not require any derivative that is why it is called zero order derivative method. This method produces good results if contraction mapping condition ($|1 - f'(X)| < 1$) is satisfied for the filter. Otherwise, the iteration becomes unstable.

3.2 R-Method

The R-method [2], originally known as the rendition algorithm is developed by minimizing the cost function:
$X^{t+1} = \alpha X^t + \lambda(J - f(X^t))$ (4)
The T-method can be considered as a special case of the R-method when α= 1 and λ=1. The convergence condition is that *f(.)* must be Lipschitz continuous [3]. The R-method can reverse the effect of a wider range of filters than the T-method. However, because of the assumptions and approximations, the R-method only performs well for filters which mildly alter the original image.

3.3 P-Method

The P-method and the S-method [4] are inspired by gradient descent methods studied by Polak [5] and Steffensen [6]. They produce effective results and converge for a larger number of linear and non-linear filters. However, they have a high computational cost due to the calculation of the 2-norm of a matrix in each iteration. The 2-norm is the largest singular value of the matrix and has a computational complexity of $O(n^2)$.

3.4 TDA Method

The TDA method [7] solves this inverse problem as minimizing a local patch-based cost function and use total derivative to approximate the gradient which is used in gradient descent. With same level of complexity as the fastest reverse filter this method is able to reverse many linear and nonlinear filters more efficiently. This method is inspired by the R-method and P-method. The difference lies in the formulation of cost function and the gradient descent.

4. Experimental Setup and Results

Experiments are conducted by introducing the gaussian blur, motion blur, and average blur in the images. The obtained blurred images are deblurred using the Zero order method [1], R-method [2], P-method [4] and TDA method [7]. The results of the Lena.jpg image with gaussian blur, motion blur, and average blur are given in the Figure 1, Figure 2, and Figure 3 respectively.

Zero order method produces good deblurring results with improved PSNR value for gaussian blur images Figure 1 (c, d). Reversing motion and average blurred image using T-method is an example of instability (Figure 2 (c, d) and Figure 3 (c, d)). Effectiveness varies based upon the complexity of filter. Details once lost during reversing cannot be revived. This method can handle only the mild blurring effect efficiently.

In case of Gaussian blur, R-method improve the blurred image slightly with no change in PSNR value in all the three cases as shown in, Figure 2 (e, f) and Figure 3 (e, f).

P-method and TDA method both perform well for all three types of blurs i.e. gaussian blur, motion blur, and average blur with improved PSNR values.

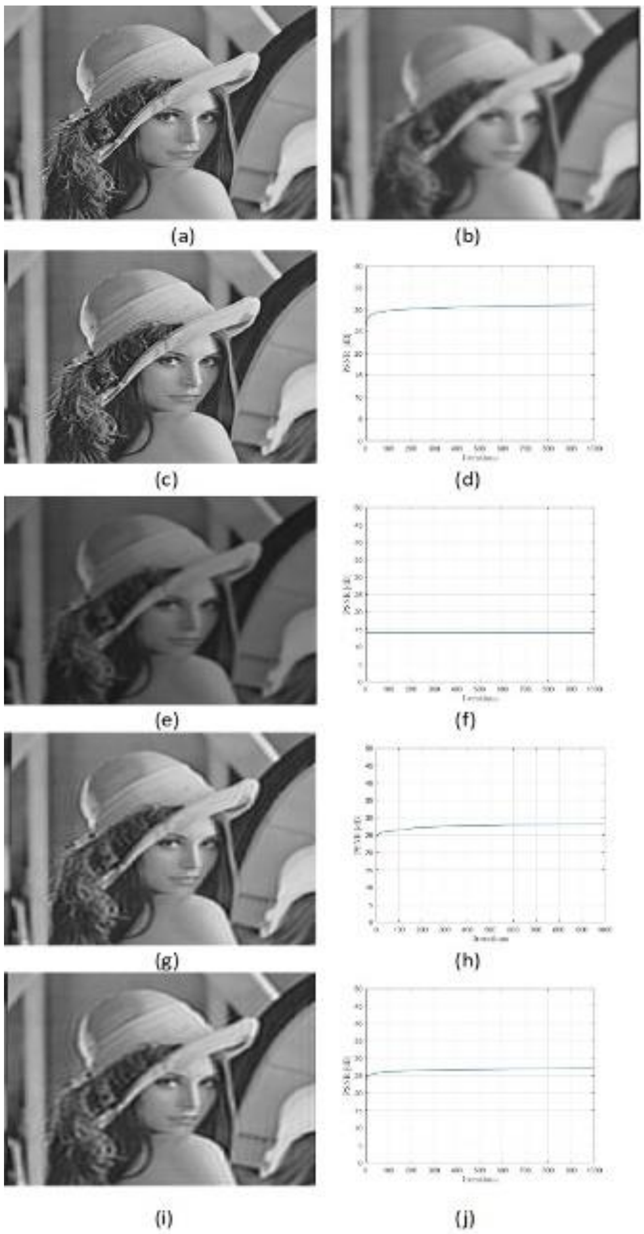

Figure 1. Deblurring Gaussian blur using different techniques (a) Original image Lena.jpg (b) Gaussian blurred image, resulting image and PSNR plot using (c, d) Zero order method, (e, f) R method, (g. h) P method, (i, j) TDA method

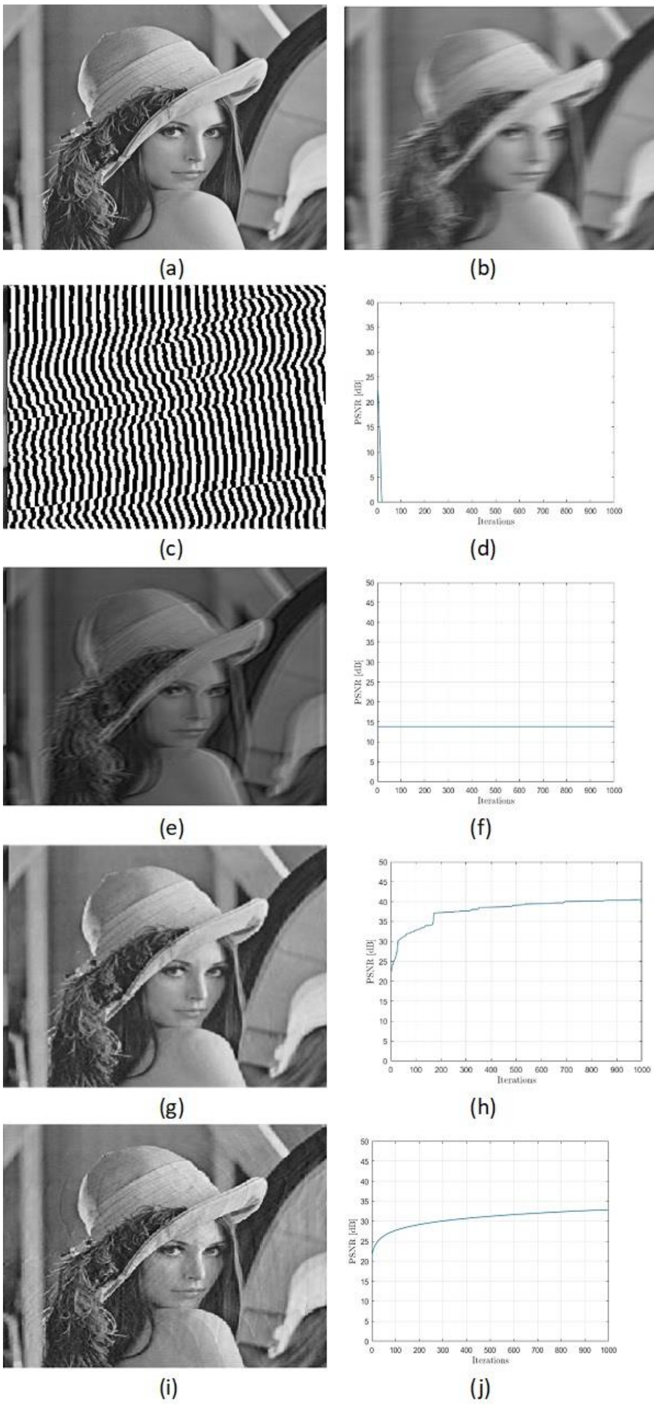

Figure 2. Deblurring motion blur using different techniques (a) Original image Lena.jpg (b) Motion blurred image, resulting image and PSNR plot using (c, d) Zero order method, (e, f) R method, (g. h) P method, (i, j) TDA method

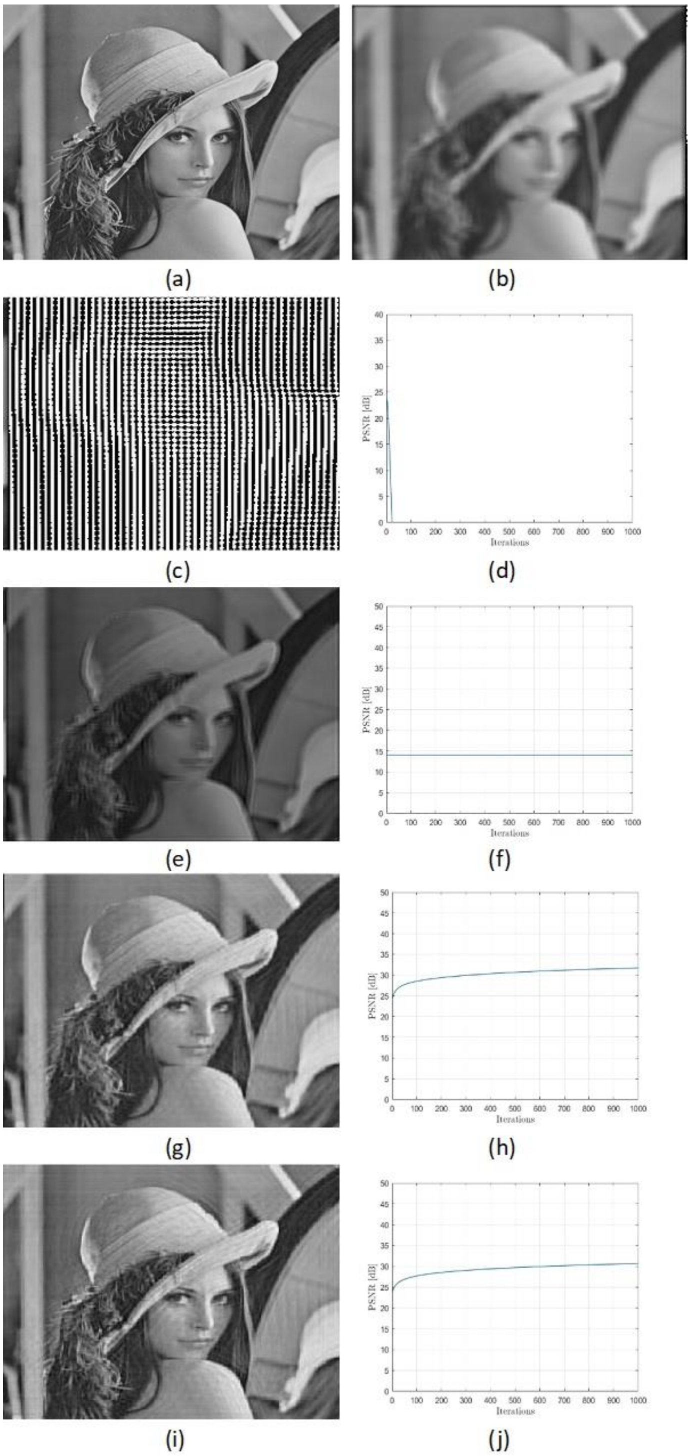

Figure 3. Deblurring average blur using different techniques (a) Original image Lena.jpg (b) Average blurred image, resulting image and PSNR plot using (c, d) Zero order method, (e, f) R method, (g. h) P method, (I, j) TDA method

5. Conclusions

Blurring reduces the visibility quality of the images. Deblurring techniques are used to enhance the quality of the blurred images. In this paper reverse filtering based deblurring techniques are analysed using images having gaussian, average and motion blur.

References

1. Tao X., Zhou C., Shen X., Wang J., & Jia J. Zero-order reverse filtering. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 222-230, 2017. https://doi.org/10.48550/arXiv.1704.04037
2. Milanfar P., “Rendition: Reclaiming what a black box takes away,” arXiv preprint arXiv:1804.08651, 2018.
3. Weaver N., Lipschitz Algebras. World Scientific Publishing Co. Pte. Ltd., 2018.
4. Belyaev A. G., Fayolle P.-A., “Two iterative methods for reverse image filtering,” Signal, Image and Video Processing, pp. 1–9, 2021.
5. Polyak B. T., “Minimization of unsmooth functionals,” USSR Computational Mathematics and Mathematical Physics, vol. 9, no. 3, pp. 14–29, 1969.
6. Steffensen J., “Remarks on iteration,” Scandinavian Actuarial Journal, vol. 1933, no. 1, pp. 64–72, 1933.
7. Galetto F. J., Deng G., "Reverse Image Filtering Using Total Derivative Approximation and Accelerated Gradient Descent," in IEEE Access, vol. 10, pp. 124928-124944, 2022, doi10.1109/ACCESS.2022.3225411.