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REVIEW ARTICLE

A Review on Various Techniques for Image Debluring

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Abstract

Image debluring refers to procedures that attempt to reduce the blur amount in a blurry image and grant the degraded image an overall sharpened appearance to obtain a clearer image. The point spread function (PSF) is one of the essential factors that needed to be calculated, since it will be employed with different types of debluring algorithms. In this paper, the studied various fast debluring techniques like Richardson – Lucy and its optimized version, Van Cittert and its enhanced version, Landweber, Poisson Map, and Laplacian sharpening filters. The usage of the PSF in the debluring algorithm is explained and a comparison between the optimized, the enhanced algorithms and Laplacian sharpening filters in terms of the number of mathematical operations, number of iterations employed, computation time, debluring in case of noise existence, and the accuracy measurement using peak signal to noise ratio (PSNR) for each technique is conducted.

1. Introduction

Captured images are considered as degraded versions of the original scene, artifacts such as blur and noise corrupt diverse sorts of images frequently. Image restoration is the process that attempts to recover the image from its corrupted version. Degraded images can be described using the following equation:

$$m = h \otimes f + n$$

Where, (m) is the degraded image, (f) is the original image, (h) is the blur operator, (n) is the additive noise and (⊗) is the convolution process. In this paper deals with blur in particular. Blur affects an image due to many reasons such as Gaussian noise degrading the image, applying a denoising algorithm on the image, imperfect resolution of the imaging system, Image data lost throughout the image acquisition procedure , and low-pass filters blur the image, while reducing the noise. The reason for doing this paper is to highlight the importance of image debluring techniques in the image processing field. For example, it is necessary to use fast debluring algorithms in surveillance systems, medical imaging systems, military applications, and digital cameras. The type of "blur" this paper will focus on is the Gaussian blur. The overall techniques of this paper consists of obtaining a clear non-degraded image, then, generates a point spread function (PSF) and convolves it with the image to form the blurry image. Moreover, additive white Gaussian noise is added to the image to simulate a blurry noisy version of the clear image. The purpose is to deblur the resulted degraded images by different fast debluring techniques, such as the optimized Richardson-Lucy, the enhanced Van Cittert, the optimized Landweber, the optimized Poisson Map and Laplacian sharpening filters.

- **Fast Blind Deconvolution**

Here, we present a fast blind deconvolution technique by reducing the computational overhead for latent image estimation and kernel estimation. For accelerating latent image estimation, we assume that the latent image has enough strong edges, and explicitly pursue sharp edge restoration and noise suppression using image filters, instead of taking a computationally expensive non-linear prior in. For kernel estimation, we accelerate the numerical optimization process by excluding pixel values in the formulation. In this method, latent image estimation is divided into two parts: simple deconvolution and prediction. Given a blurred image B and kernel K, we first remove the blur to obtain an estimate L of the latent image using simple and fast deconvolution with a Gaussian prior. Due to the characteristics of a Gaussian prior, L would contain smooth edges and noise in smooth regions. In the prediction step, we obtain a refined estimate L0 by restoring sharp edges and removing noise from L with efficient image filtering techniques. As a result, L0 provides a high-quality latent image estimation needed

II. DEBLURING TECHNIQUES

A. Lucy- Richardson Algorithm Technique:

The Richardson–Lucy algorithm, we also called as Richardson–Lucy deconvolution, is an iterative procedure for recovering a latent image that has been the blurred by a known PSF.

$$C_i = \Sigma_j \, p_{ij} u_j$$

Where: p_{ij} is the point spread function (the fraction of light coming from true location j that is observed at position i) u_j is the pixel value at location j in the latent image, and c is the observed value at pixel location i. The statistics are performed under the assumption that u_j are Poisson distributed, which is appropriate for photon noise in the data. The basic idea is to calculate the u_j given the observed c_i and known p_{ij}.

This form an equation for uj which can be solved iteratively according to:

$$u_j = u_j^t \Sigma j \frac{c_i}{c_i} p_{ij}$$

Where

$$C_i = \Sigma_j u_j^t . p_{ij}$$

It has been shown that if this iteration converges, it converges to the maximum likelihood solution for uj.

- **Point Spread Function(PSF)**

Point Spread Function (PSF) is means the degree to which an optical system blurs (spreads) a point of light. In the PSF the inverse Fourier transform of Optical Transfer Function (OTF) in the frequency domain, the OTF describes the response of a linear, position-invariant system to an impulse.OTF is the Fourier transfer of the point (PSF).

B. Blind Deconvolution Technique:

There are two types of deconvolution methods. They are projection based blind deconvolution and maximum likelihood restoration. In the first method it simultaneously restores true image and point spread function. This begins by making initial estimates of the true image and PSF. The technique is cylindrical in nature. Firstly we will find the PSF estimate and it is followed by image estimate. This cyclic process is repeated until a predefined convergence criterion is met. The advantage of this method is that it appears robust to inaccuracies of support size and also this method is insensitive to noise. The problem here is that it is not unique and this method can have errors associated with local minima. In the second approach the maximum likelihood estimate of parameters like PSF and covariance matrices. As the PSF estimate is not unique other assumptions like size, symmetry etc. of the PSF can be taken into account. The main advantage is that it has got low computational complexity and also helps to obtain blur, noise and power spectra of the true image. The drawback of this approach is that algorithm being converging to local minima of the estimated cost function.

C. Debluring with Blurred/Noisy Image Pairs:

In this method the image is deblurred with the help of noisy image. As a first step both the images the blurred and noisy image are used to find an accurate blur kernel. It is often very difficult to get blur kernel from one image. Following that a residual deconvolution is done and this will reduce artifacts that appear as spurious signals which are common in image deconvolution. As the third and final step the remaining artifacts which are present in the non-sharp images are suppressed by gain controlled deconvolution process. The main advantage of this approach is that it takes both the blurred and noisy image and as a result produces high quality reconstructed image. With these two images an iterative algorithm has been formulated which will estimate a good initial kernel and reduce deconvolution artifacts. There is no special hardware is required. There is also disadvantage with this approach like there is a spatial point spread function that is invariant.

D. Debluring with Motion Density Function:

In this method image debluring is done with the help of motion density function. A unified model of camera shake blur and a framework has been used to recover the camera motion and latent image from a single blurred image. The camera motion is express as a Motion Density Function (MDF) which records the fraction of time spent in each discretized portion of the space of all possible camera poses. Spatially varying blur kernels are derived directly from the MDF. One limitation of this method is that it depends on imperfect spatially invariant debluring estimates for initialization.

E. Debluring with Handling Outliers:

In this method various types of outliers such as pixels saturation and non-Gaussian noise are analysed and then a deconvolution method has been proposed which contains an explicit component for outlier modeling. Image pixels are classified into two categories: Inlier pixels and Outlier pixels. After that an Expectation Maximization method is employed to iteratively refine the outlier classification and the latent image.

F. Debluring by ADSD-AR:

In this approach ASDS (Adaptive Sparse Domain Selection) scheme is introduced, which learns a series of compact sub-dictionaries and assigns adaptively each local patch a sub-dictionary as the sparse domain. With ASDS, a weighted l1-norm sparse representation model will be proposed for IR tasks. Further two adaptive regularization terms has been introduced into the sparse representation framework. First, a set of autoregressive (AR) models are learned from the dataset of example image patches. The best fitted AR models to a given patch are adaptively selected to regularize the image local structures. Second, the image nonlocal self-similarity is introduced as another regularization term.

G. Neural Network Approach:

Neural networks is a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, adaptive interaction between elements, When an element of the neural network fails, it can continue without any problem by their parallel nature. ANN provides a robust tool for approximating a target function given a set input output example and for the reconstruction function from a class a images. Algorithm like the Back propagation and the Perceptron use gradient- decent techniques to tune the network parameters to best-fit a training set of input-output examples. We are using Back propagation neural network approach for image restoration. This approach is capable of learning complex non-linear functions is expected to produce better structure especially in high frequency regions of the image. We used a two layer Back propagation network with full connectivity.

IV. Comparison of Different Debluring Techniques

This work makes a comparison between different debluring techniques. Following are tabular results obtained after the comparison.

Table1. COMPARISON TABLE

Methods Used	Types of Blur	Performance	PSNR Value
Wiener filter	Gaussian	Worst Result	17.06
Lucy-Richardson	Gaussian	Efficient	21.02
Blind Image Deconvolution	Motion	Efficient	26.76
Using MDF	Motion	Efficient	24.30
Using Handling Outliers	Gaussian	Efficient	21.91
Using ASDS-AR	Gaussian	Very Efficient	31.20
Neural Network	Gaussian, Out-of-focus	Very Efficient	30.10

V. Conclusion

From the above analysis we can see that though the subspace analysis and blind image deconvolution finds result to some extent it is prone to errors and is more or less like a probability method. In the local phase quantization technique it is accurate but not robust to different types of blurs and lighting problems can make the debluring difficult. In the Set theoretic approach we can see that it is more accurate and different blur conditions are added on to make deconvolution method much less complex than the other approaches.

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