CONVOLUTIONAL DEBLURRING FOR NATURAL IMAGING

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ABSTRACT

Here, we tried to implement the Convolutional Deblurring for Natural Imaging paper by Mahdi S. Hosseini and Konstantinos. In the paper, they suggest a new way to fix blurry images by using a one-step convolution filter that can be used directly on naturally blurry images to make them clear again. Optical blurring is a problem that many imaging applications that have optical flaws have in common. The main problem with deblurring in a single shot is that it takes a lot of time and a lot of computing power. They close this gap by making a deconvolution kernel as a linear combination of finite impulse response (FIR) even-derivative filters. This kernel can be directly convolved with blurry input images to increase the frequency fall-off of the point spread function (PSF) associated with optical blur. They use a Gaussian low-pass filter to separate the problem of image edge deblurring from the problem of image noise removal.

***Index Terms*—** Point Spread Function(PSF), Image Deconvolution, Finite Impulse Response(FIR), Opical Blur, Generalised Gaussian.

1. INTRODUCTION

In an optical system that is not ideal, a beam of light that travels through the optical apparatus will not be converted to a single end point but rather will instead spread out across the image domain. The term "point spread function" refers to the effect of spreading that occurs here (PSF).

$$f_B(x) = f_L(x) * h_{PSF}(x) + \eta(x) \qquad (1)$$

the latent sharp image (image to be recovered), h_{PSF} is the associated PSF kernel, and is the noise contamination artifact.

When the PSF is provided, this type of image deconvolution problem is referred to as the "non-blind" deconvolution; otherwise, it is referred to as the "blind" donvolution. The blind strategy was utilised in the paper that they wrote. It is usual for the energy of the high frequency band to taper off, and this is one of the factors that contributes to the fuzziness of the point spread function (PSF). To a large extent, aberrations, such as turbid medium and out-of-focus, can be recognised by a point spread function (PSF) that is symmetric. This PSF preserves the image geometry and is known to be a common issue in a variety of imaging modalities.

In order to solve the real-time acquisition issue, a more practical strategy would be to incorporate fast deblurring methods such unsharp masking techniques. Although such masks do not require any additional processing cost than that of a one-shot filter convolution, they do not necessarily comply with the inverse response of the PSF for fall-off correction. As a result, the image quality that they create is subpar and has defects of oversharpening.

In this study, we concentrate on the appropriate method for correcting the fall-off frequency in the PSF by casting image deconvolution as a problem involving a one-shot convolution filter. Our approach can be broken down into two primary stages. In the first step, we get to the conclusion that the a priori PSF model may be inferred through a scale-space analysis of the blurred image in the Fourier domain. After making an assumption regarding the frequency fall-off of natural images, we then blindly estimate the statistics of the point spread function (PSF) for a distinct Gaussian model. In the second step, we provide a closed-form solution to the inverse PSF for deblurring. To do this, we first fit a series of polynomials in the frequency domain, and then we obtain its equivalent representation in the spatial domain as a linear combination of FIR derivative filters. This allows us to deblur the image in a way that is more accurate.

2. CHALLENGES AND CONTRBUTIONS

When it comes to practical implementation, high speed recovery simply refers to the use of a "noniterative" technique (or at least, very few procedural algorithms). There aren't many solutions like this one, and the ones that do exist tend to be sped up using fast Fourier transform (FFT) algorithms like Wiener, Cho, and Lee Richardson-Lucy as well as diagonalizing-based algorithms.

These algorithms are, however, still constrained by the blur modelling of natural images. In addition, the vast majority of deconvolution methods include convoluted procedures for parameter adjustment. The following are the contributions that this paper makes toward tackling the aforementioned challenges:

- According to our observations, the issues of image denoising and deblurring ought to be treated independently when it comes to reconstruction. For the purpose of image correction, we define a dual spatial domain. To be more specific, we come up with a closed-form solution of the deblurring kernel by designing it as a linear combination of high-order FIR even-derivative filters. We utilise the MaxPol library in order to carry out the numerical implementation. Before attempting to estimate the sharpness of the deblurred edges, we consider using a generalised Gaussian filter for smooth denoising.

- In order to model, we make use of the generalised Gaussian distribution.PSF blur, as well as an analysis of its practicable range for recovery utilising the deblurring method that was proposed. Many PSF are the ones responsible for such a consideration (static blur) applications are symmetrical, and they can be modelled using such distribution.

- The estimation of PSF should be done blindly for a specific purpose. A new blind PSF estimate method is formulated by the authors using analysis of scale space performed in the Fourier domain When making a blind estimate of blur statistics, the Gaussian model is one option we evaluate. This type of blind estimating is used in a variety of applications including imaging satellites, there is no other method that is practically viable for PSF. Calibration is necessary, and as a result, a blind estimate must be made.

3. PROPOSED DECOUPLED APPROACH.

In this section, they will discuss a new method for symmetric PSF deblurring, which will involve correcting the fall-off of the high frequency band using frequency polynomial approximation. Recall that the Wiener deconvolution results in the generation of a filter denoted by $h_W(x)$ in such a way that the direct convolution of this filter with the observed image results in a closed approximation of the latent image denoted by $\bar{f}_L(x) = h_W(x) f_B(x)$. This filter is generated by finding the point in the Fourier domain where the mean square error between the latent image f_L and the recovered (approximate) image is the smallest in the Fourier Domain.

$$\hat{\epsilon}(\omega) = \mathbf{E}\left|\hat{f}_L(\omega) - \hat{\bar{f}}_L(\omega)\right| \quad (2)$$

By substituting $\hat{\bar{f}}_L()$ in (2) and minimizing the error with respect to latent image, the associated filter will be expressed by

$$\hat{h}_w(\omega) = \frac{1}{\hat{h}_{PSF}(\omega)} \hat{h}_{LPF}(\omega) \quad (3)$$

$$\hat{h}_{LPF}(\omega) = \frac{\left|\hat{h}_{PSF}(\omega)\right|^2}{\left|\hat{h}_{PSF}(\omega)\right|^2 + 1/SNR(\omega)}$$

. The numerical implementation of the Wiener filter is typically carried out by transferring the blur image observation into the Fourier domain, manipulating the frequency responses in accordance with the filter definitions in (3), and recovering the image by using the inverse Fourier transform. This process is repeated until the desired result is achieved. On the other hand, the Gibbs phenomenon, commonly referred to as ringing artefacts, can occur while performing an inverse transform.

The primary goal that they wish to accomplish with this approach is to isolate the processes of denoising and blur correction in (3) by designing two distinct convolutional filters in the dual spatial domain.

$$h_D(x) = h_{PSF}^{-1}(x) * h_{Denoise}(x) \quad (4)$$

such that the convolution of the decoupled filter $h_D(x)$ in (4) with the blurry observed image yields the latent approximation $\hat{f}_L(x) = h_D(x) * f_B(x)$. The merit of our design in (4) is the decoupling of the denoising and deblurring problems, enabling them to be individually addressed for recovery. One can separately apply a denoiser as a plug-in tool if the input image is perturbed with noise.

3.1. Inverse Deconvolution Kernal Design

The inverse PSF response is approximated in the Fourier domain by a series of frequency polynomials, which allows us to establish a dual representation in both the Fourier and spatial domains.

$$\frac{1}{\hat{h}_{PSF}(\omega)} \approx \sum_{n=0}^{N} \alpha_n \omega^{2n} \quad (5)$$

We only evaluated even polynomials for approximation since the symmetry of the PSF ensures that the inverse response will be an even function. This led us to only investigate even polynomials. The inverse PSF response is fitted to a polynomial series up to a specified frequency range, which allows for the determination of the unknown coefficients $\alpha_n{}_{n-1}^{N}$.

A linear combination of derivative operators is comparable to the dual representation of frequency polynomials that are found in the spatial domain. Consequently, the dual form of the inverse filter defined in equation (5) can be similarly represented by

$$h_{PSF}^{-1}(x) \approx \delta(x) + \sum_{n=1}^{N} \alpha_n (-1)^n \frac{\partial^{2n}}{\partial x^{2n}} \quad (6)$$

Take note that the assumption that the energy of the PSF has been normalised $\int h_{PSF}(x)dx = 1$ in (6), which is a step that is distinct from the deconvolution process. It is possible to obtain a numerical approximation of the continuous derivative operators in equation (6) by using finite impulse response (FIR) convolution filters.

$$h_{PSF}^{-1}[k] = \delta[k] + D[k] \tag{7}$$

where $D[k] = \sum_{n=1}^{N} \alpha_n (-1)^n d^{2n}[k]$ is the deblurring kernel.$d^{2n}[k]$ is the discrete approximation to the 2n-th order derivative operator applied in the bounded continuous domain x ∈ [T, T] ,i.e. $d_{2n}(x) \equiv \delta^{2n}/\delta x^{2n}$. We have used MaxPol which provides a closed-form solution to FIR derivative kernels that can be regulated in terms of different parameter designs.

3.2. Decoupled Smoothning Filter.

The purpose of the decoupled design in equation (4) is to balance in amplitude fall-off high-frequency components that is a result of the PSF kernel. After using an inverse filter to deconvolve the picture, the next step in the denoising process is to apply (convolve) similar symmetric blur kernels with a lower blur scale than the one that was evaluated for deconvolution. For this kind of denoising, we recommend employing a generalised Gaussian kernel because the associated FIR kernel does not have a vanishing moment and, as a result, does not result in edge hallucinations.

3.3. Two dimensional deblurring framework.

While our design in the previous section is applied in one dimension, for imaging applications this should be extended to two dimensions (2D). Let $f(x,y) \in R^{N_1 \times N_2}$ represent the image in the 2D domain, with N1 and N2 being the number of discrete pixels along the vertical and horizontal axes, respectively. The PSF blur is believed to be rotationally symmetric in many optical imaging systems, which means that the associated blurring operator is the same in any arbitrary rotational angle, i.e. $h_{PSF}(r,\theta) = h_{PSF}(r)$. For instance the Gaussian like PSF kernel $h_{PSF}(r,\theta) = 1/\sqrt{2\pi\sigma^2} e^{-r^2/2\sigma^2}$ is rotationally invariant. In in fact, the Gaussian point spread function can be generated using two distinct kernels that run along the horizontal and vertical axes of the Cartesian coordinate system, e.g. $h_{PSF}(x,y) = 1/\sqrt{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} h_{PSF}(x) h_{PSF}(y)$ . . In general, we assume the the blur operator is independently applied in both dimensions (separable mode).So, the linear model in (1) is revised to

$$f_B(x,y) = f_L(x,y) * h_{PSF} * h_{PSF}(y) + \eta(x,y) \tag{8}$$

. The approximation method described in the preceding section is used to build the relevant deblurring kernels in both directions, and then those kernels are applied to the blurry image in order to reconstruct it.

$$f_R(x,y) = h_D(x) * h_D(y) * f_B(x,y) \tag{9}$$

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The energy level of the blurring kernal is known a priori for natural image problems. We define a tuning parameter $\gamma \in [0,1]$ to control the deconvolution level,

$$f_R(x,y) = f_B(x,y) + \gamma \bigtriangledown_D f_B(x,y) \tag{10}$$

where $\bigtriangledown_D f_B(x,y) = f_B(x,y) * [D_x + D_y + D_{xy}]$ ives us the reconstructed image edge and $D_{xy} = D_x * D_y$.

3.4. Adaptive Level Tuning.

Calculating the relative ratio of two images' entropy values allows us to develop an adaptive metric that allows us to control the significance level of γ,

$$\gamma \doteq \frac{E(f_B)}{E(\bigtriangledown_D F_B) + T} \tag{11}$$

where $E(I) = -\sum_{k \in \Omega} p(k)\ log\ p(k)$ is the Entropy of the input image and p(k) is the histogram count for grey level k. The threshold T is defined to avoid singularities due to sparse deblurring edges.

4. BLUR MODELLING AND ESTIMATION

We simulate the point spread function blur kernel in natural imaging applications using the generalised Gaussian (GG) distribution in this section. We investigate Gaussian model shape as particular examples of GG for blind estimating.

4.1. Modelling blur by Generalised Gaussian(GG).

Subbotin proposed the generalised Gaussian (GG) distribution in order to rewrite the power law of Gauss's distribution into a more generalised sense. GG stands for the generalised version of the Gaussian distribution.

$$h_{GG}(x) = \frac{1}{2\Gamma(1+1/\beta)A(\beta,\sigma)} exp - \left| \frac{x}{A(\beta,\sigma)} \right|^{\beta}$$

(12)

where β defines the shape of the distribution function, $A(\beta,\sigma) = (\sigma^2 \Gamma(1/\beta)/\Gamma(3/\beta))^{1/2}$ is the scaling parameter and $\Gamma(.)$ is the Gamma Function.

Modeling static blur in natural imaging, such as that caused by atmospheric turbulence and optical aberrations, is the primary function of the GG model, which is used in a variety of imaging applications. The use of such kernel in a manner that is not blind is a frequent strategy taken when picture deconvolution is being performed. The form and the scale are the two distinct properties that are appropriate for a variety of applications involving blur.

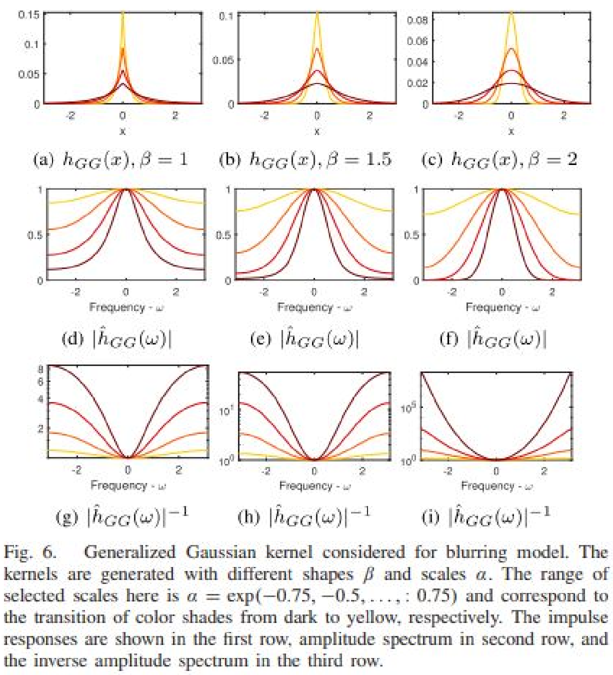

Fig. 1. Generalized Gaussian blur Kernel.

4.2. Blur PSF Estimation.

In this section we introduce our blind approach to estimate the blur level of the PSF kernel from naturally blurred images. Our approach relies on image scale-space analysis using two different scales that are the originally sampled image $f_B(x, y)$ and its down-sampled version $f_B(sx, sy)$ for s ¿ 1. $\hat{f}_B(r/s, \theta)$ can be found by

$$\int_0^{2\pi} \hat{f}_B(r/s, \theta) d\theta \approx \int_0^{2\pi} \frac{s}{r} \hat{h}(r/s, \theta) d\theta + c \qquad (13)$$

where c is a function of the SNR.

The 2-d blur Gaussian blur kernel is defined by $h(x, y) = \frac{1}{2\pi\alpha^2} exp - (x^2 + y^2)/2\alpha^2$ and its 2-d Fourier Transform is defined by $\hat{h}(\omega_x, \omega_y) = exp - \alpha^2/2(\omega_x^2 + \omega_y^2)$.

Converting to cartestan domain we get $\hat{h}(r) = exp - \alpha^2 r^2/2$. and substituting in the ratio spectrum we have the simplification as

$$R(r) \approx \frac{exp - \alpha^2 r^2/2 + c' r}{s\ exp - \alpha^2 r^2/2s^2 + c' r} \qquad (14)$$

5. OUTPUT

Fig. 2. Cameraman Image which is a Grey-Scale image being deblurred.

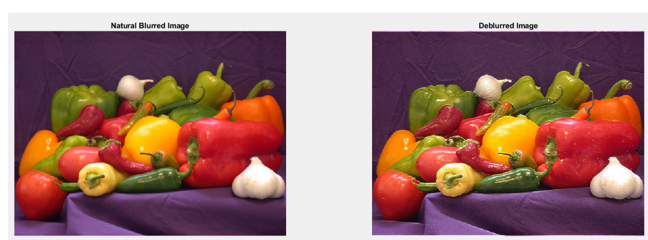

Fig. 3. Peppers Image which is a RGB image being deblurred.