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Reduction of Image Blurring With Digital Filters

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ABSTRACT
In digital photography image blurring is one of the general artifacts. Digital filters and algorithm is well-known for deblurring the image. This paper proposed different filters and algorithm like inverse filter, wiener filter and an improved Lucy-Richardson deconvolution algorithm. Before deconvolution step, we separate the blurred image into smooth part. By introducing different noises and image corrupting parameters scale and length the blurred image are then used for image deblurring. The filter comparison provides the different parameter which decided the image quality and best result.
Keywords - Inverse Filter, Wiener Filter, Lucy-Richardson Algorithm.

I. INTRODUCTION

Taking handheld photos in low-light conditions is challenging. Since less light is available, longer exposure times are needed – and without a tripod, camera shake is likely to happen and produce blurry pictures. Increasing the camera light sensitivity, i.e., using a higher ISO setting, can reduce the exposure time, which helps. But it comes at the cost of higher noise levels. Further, this is often not enough, and exposure time remains too long for handheld photography, and many photos end up being blurry and noisy.

Many single image blind deconvolution methods have been recently proposed. Although they generally work well when the input image is noise-free, their performance degrades rapidly when the noise level increases. Specifically, the blur kernel estimation step in previous deblurring approaches is often too fragile to reliably estimate the blur kernel when the image is contaminated with noise. Even assuming that an accurate blur kernel can be estimated, the amplified image noise and ringing artifacts generated from the non-blind deconvolution also significantly degrade the results i.e blurred image.

Our approach is derived from the key observation that if a directional low-pass linear filter is applied to the input image, it can reduce the noise level greatly, while the frequency content, including essential blur information, along the orthogonal direction is not affected. We use this property to estimate 1D projections of the desired blur kernel to the orthogonal directions of these filters.[13]

1.1 Image Deblurring

This section provides some background on deblurring techniques. The section includes these topics:

• Causes of Blurring
• Deblurring Model

1.2 Causes of Blurring

The blurring, or degradation, of an image can be caused by many factors:

- Movement during the image capture process, by the camera or, when long exposure times are used, by the subject.
- Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduces the number of photons captured.
- Scattered light distortion in confocal microscopy.

1.3 Using the Deblurring Function

The toolbox includes four deblurring functions, listed here in order of complexity:

a. deconvwnr : Implements deblurring using the Wiener filter.
b. deconvreg : Implements deblurring using a regularized filter.
c. deconvlucy: Implements deblurring using the Lucy-Richardson algorithm.
d. deconvblind: Implements deblurring using the blind deconvolution algorithm.

All the functions accept a PSF and the blurred image as their primary arguments. The deconvwnr function implements a “least squares solution”. The deconvreg function implements a constrained least squares solution, where it can place constraints on the output image (the smoothness requirement is the default). With either of these functions, it should provide some information about the noise to reduce possible noise amplification during deblurring. The deconvlucy function implements an accelerated, damped Lucy-Richardson algorithm. This function performs multiple iterations, using optimization techniques and Poisson statistics. With this function, we do not need to provide information about the additive noise in the corrupted image.

Deconvwnr Implements deblurring using the Wiener filter deconvreg Implements deblurring using a regularized filter deconvlucy Implements deblurring using the Lucy-Richardson algorithm Deconvblind implements deblurring using the blind deconvolution algorithm[1]

The Richardson–Lucy algorithm, also known as Lucy–Richardson deconvolution, is an iterative procedure for recovering a latent image that has been blurred by a known point spread function. Pixels in the observed image can be represented in terms of the point spread function and the latent image. Use the deconvlucy function to deblur an image using the accelerated, damped, Lucy-Richardson algorithm. The algorithm maximizes the likelihood that the resulting image, when convolved with the PSF, is an instance of the blurred image, assuming Poisson noise statistics. This function can be effective when you know the PSF but know little about the additive noise in the image. The deconvlucy function implements several adaptations to the original Lucy-Richardson maximum likelihood algorithm that address complex image restoration tasks.

1.4 Previous work

The filtering approach for image deblurring has providing the good results with various digital filters for digitizing the images ,as the result get noise free and informatics. Image deblurring 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 cleared image. The point spread function (PSF) is one of the essential factors that needed to be calculated. Improved quality of blurred images has been introduced by telatar.

The proposed method is based on the estimation of the multi-criteria information of the degraded images. The filter coefficient is then estimated using the edge information of the degraded image. Experiments have been conducted using simulated and real world images to evaluate the performance of the proposed method and the results are presented.[12] Image Deblurring – Wiener Filter Versus TSVD Approach paper by P. Bojarczak and Z. Łukasik has introduced the working with performance comparison of Wiener Filter and TSVD Approach. Wiener filter is a method giving the best results when variance of the noise incorporated in blurring process is known a priori . In TSVD decomposition the knowledge of precise variance of the noise is not necessary to image restoration.

The paper also discusses basis blurring forms and their mathematical description. TSVD method has an advantage allowing for the estimation noise level of the image on the basis of Picard plot, what makes it attractive in application where the information about noise is not available a priori. On the other hand w hen the detailed information about noise level of image is well known, then Wiener filter seems to be a better solution.

II. ITERATIVE METHODS OF RICHARDSON-LUCY-TYPE FOR IMAGE DEBLURRING

Image deconvolution problems with a symmetric point-spread function arise in many areas of computer science and engineering. These problems often are solved by the Richardson-Lucy method, a nonlinear iterative method. First it shows a convergence result for the Richardson-Lucy method. The proof sheds light on why the method may converge slowly. Subsequently, it describes an iterative active set method that imposes the same constraints on the computed solution as the Richardson-Lucy method. Computed examples show the latter method to yield better restorations than the Richardson-Lucy method and typically require less computational effort.

2.1 Lucy-Richardson (LR) Method:

The Lucy-Rechardson method is based on the iterative active set scheme described in [10] for finite dimensional problems. We therefore consider a discretization

$$Ax = b^{\delta} \quad (2.1)$$

Let the available image that we would like to restore be represented by an n × n array of pixels. Ordering these pixels column-wise yields the right-hand side $b^{\delta} \in Rm$ of (2.1) with $m = n2$. The matrix $A \in Rm \times m$ in (2.1) represents a discretization of the integral operator in (1.4), and the entries of $x \in Rm$ are pixel values, ordered column-wise, of an approximation of the desired blur- and noise-free image.
The entries of b□ are contaminated by noise.
Let $b \in Rm$ be the associated vector with the unknown noise-free entries, i.e.,

$$b^{\delta} = b + \eta^{\delta}$$
$$(2.2)$$

where the vector η represents the noise. In the present section and in the computed examples, we will assume that a fairly accurate bound

$$k\eta^{\delta}k \le \delta$$
$$(2.3)$$

is known, where k · k denotes the Euclidean vector norm, and that the linear system of equations with the noise-free right-hand side,

$$Ax = b$$
$$(2.4)$$

is consistent.

Let $x^{\Lambda} \in Rm$ denote the solution of minimal Euclidean norm of (2.4). We are interested in computing an approximation of x^{Λ} that satisfies discrete analogues of the constraints image function .

The iterative active set method in [10] is designed to determine an approximate solution of the constraint minimization problem

$$\min kAx - b^{\delta}k,\ x \in S$$

where $S \subset Rm$ is a convex set of feasible solutions defined by box constraints. A vector $x \in Rm$ is said to satisfy the discrepancy principle if

$$kAx - b^{\delta}k \le \gamma\delta,$$
$$(2.5)$$

where $\gamma > 1$ is a user-chosen constant. The size of γ depends on the accuracy in the estimate δ. If δ is known to be a tight bound for the norm of the noise, then γ is generally chosen to be close to unity. We note that the vector xˆ satisfies (2.5).

The active set method [10] first determines an approximate solution of (2.1) with the LSQR iterative method. This is a minimal residual Krylov subspace method; see [11] for details. We use the initial iterate x0 = 0 and terminate the iterations as soon as an iterate xk that satisfies the discrepancy principle (2.5) has been found.

The vector xk is not guaranteed live in S. The scheme [10] therefore projects xk orthogonally into S and if necessary applies an active set method to determine an approximate solution of (2.1) that lies in S and satisfies the discrepancy principle. The active set method uses LSQR. We have found it useful to iterate with LSQR until the discrepancy principle (2.5) is satisfied after each update of the active set. Each update generally affects several of the components of the computed approximate solutions[10]. A related method and theoretical results are shown in [9].

Now it describe how the outlined active set method can be applied to enforce a constraint analogous to (1.6). Define the norm

$$m$$
$$x = [x1, x2, ...$$
$$kxk1 = |xj|, xm]T$$

III. EFFECTS OF IMAGE NOISE IN MOTION DEBLURRING

For simplicity, assume that the motion blur kernel is spatially invariant and the effects of motion blur and image noise to be modelled by the following convolution equation:

$$y = k \otimes x + n(1) \qquad (3.1)$$

where y is the observed noisy and blurry image, x is the latent image, k is the motion blur kernel and n is image noise.

The Fourier transform of Equation (3.1) to the frequency domain is expressed using capital letters:

$$Y = KX + N(2) \qquad (3.2)$$

The problem of motion deblurring is highly ill-posed since the number of unknowns (x, k and n) exceeds the number of equations that can be derived from the observed data(y). To simplify the problem, many previous works assume the input image to contain negligible noise so that the effect of n can be disregarded or suppressed by regularization in the blur kernel and latent image estimation processes.[11]

3.1 Inverse & Winner filter

Inverse filter restores a blurred image perfectly from an output of a noiseless linear system. However, in the presence of additive white noise, it does not work well. This project demonstrated how the ratio of spectrum N/H affects on the image restoration.

The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. From a signal processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgram of intensities from points along the line of the camera's motion. This is a two-dimensional analogy to the Wiener filter is a linear filter. It assumes that the image is blurred with a Gaussian shaped kernel and noised by Gaussian distribution. The filter tries to minimize the mean square error between the image acquired and its restored estimate. The Wiener filter operates in the Fourier Space. It can be stated as followed:

$$X_w(\mathrm{u}) = \frac{Y(\mathrm{u})}{H(\mathrm{u})} W(\mathrm{u}) \tag{3.3}$$

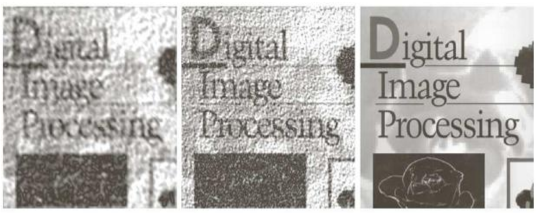
Here, Y is the observed image, H the point spread function, X the reconstructed Wiener image and 1 / H(u) is the raw inverse filter. W(u) is the zero-phase filter defined by:

$$W(\mathrm{u}) = \frac{P_{H(\mathrm{x})}(\mathrm{u})}{P_{H(\mathrm{x})}(\mathrm{u}) + \mathrm{P}_{N(\mathrm{u})}} \tag{3.4}$$

Here, $P_{H(x)}$ is the power of the noiseless image and $P_{N(u)}$ the power of the noise. One can see that W(u) is used to remove the present noise and the term 1 / H does the deblurring. The resulting image from the Wiener filter is obtained by an inverse Fourier transform of $X_{W(u)}$.

A benefit of the Wiener filter is that even a sloppy determination can still give excellent results, even though the method is not as sophisticated.[12]

1) Comparison result of a) Full inverse b) Radially inverse c) Wiener filter



2) Comparison of Wiener and constrained least squares filtering

Fig 3.1 Inverse & winner filters results

IV. RESULT

Affecting the deconvolution results by providing values for the optional arguments supported by the deconvwnr function. Using these arguments we can specify the noise-to-signal power value and or provide autocorrelation functions to help refine the result of deblurring. To see the impact of these optional arguments, view the Image Processing Toolbox deblurring demos. Deblurring with a regularized filter use the deconvreg function to deblur an image using a regularized filter. A regularized filter can be used effectively when limited information is known about the additive noise. To illustrate, this example simulates a blurred image by convolving a Gaussian filter PSF with an image (using imfilter). Additive noise in the image is simulated by adding Gaussian noise of variance V to the blurred image (using imnoise). Fig. 4.1 shows the comparison between inverse filter, winner filter and Lucy-Richardson algorithm.

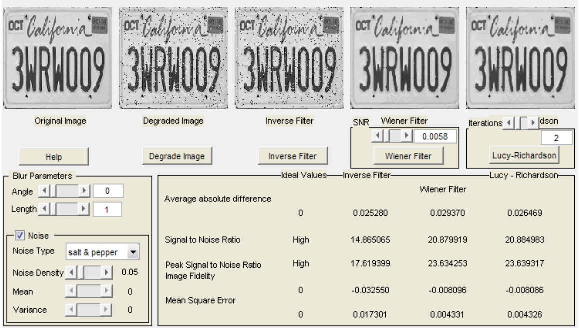


Fig 4.1 Filters comparison

V. CONCLUSION

The computed examples show the proposed active set method with the discrepancy principle as stopping criterion to yield restorations of higher quality than any restoration determined by Richardson-Lucy. Moreover, for most examples computation the best restoration with the latter method required more matrix-vector product.

Qualitative perceptual tests indicate that the algorithm in its current form reduces the amount of perceptible blur. Looking towards the future, we see our algorithm and digital filter bank contributing to the improved image quality.

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