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A STUDY ON IMAGE RESTORATION AND EFFECT OF BLIND DE-CONVOLUTION ALGORITHMS

K. Sunil Manohar Reddy[1]; Prof. BK Tripathi[2]; Dr. S. K. Tyagi[3]
[1]Assistant Professor, Dept. of CSE, MECS, Hyderabad
[2]Professor, Dept. of CSE, HBTU, Kanpur
[3]Professor, Dept. of CSE, CCSU, Meerut

Abstract- Motion blur is an unavoidable tradeoff between the measure of blur and the measure of noise in the procured images. The effectiveness of any rebuilding calculation ordinarily relies upon these amounts, and it's hard to locate their best balance so as to facilitate the reclamation work, while the Point-Spread-Function (PSF) trajectories as random processes, expresses the restoration performance. The intention for restoration error is adapted on some motion-randomness descriptors and also exposure time. By utilizing blind de-convolution algorithms with assessed PSF on single-picture; blur kernel is legitimately evaluated from light streaks in the obscured image. Consolidating with the sparsity constraint, blind de-convolution algorithms and greatest probability estimation approach, it very well may be settled rapidly and precisely from a user input picture. This blind kernel (PSF) would then be able to be applied to single-image to reestablish the sharp image. This paper portrays idea of Image Restoration and Blind De-convolution Algorithms with different images.
Keywords- Image Restoration, De-Convolution, Point Spread Function

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I. INTRODUCTION

Digital image processing is the use of computer algorithm to implement image processing on digital image. In inverse fields from planetary science to molecular spectroscopy and medical imaging to satellite imaging, the issue of recovering original images from blurred and noisy images is difficult [9]. All natural images when displayed, have gone through some kind of degradation throughout the display mode, acquisition mode, or processing mode .The degradations may be because of sensor noise, blur due to camera misfocus, relative object camera motion, random atmospheric turbulence, others. In many of the present image restoration techniques, the degradation process can be explained using a mathematical model. A simplified version for the image restoration process model is given as:

$$y(i, j) = H[f(i, j)] + n(i, j),$$

Where

y(i, j) The degraded image

f(i, j) The original image H,an operator that represents the degradation process.

n(i, j) The external noise which is assumed to be image-independent.

II. IMAGE RESTORATION

The purpose of image restoration is to compensate defects that facilitate degrading an image. In cases such as motion blur, it is feasible to come up with a suitable estimate of the actual blurring function and eliminate the blur to restore the actual image. In cases when the image is corrupted by noise, the best is to compensate for the degradation it caused. [2]

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Figure 1. Before Restoration

Figure 2. After Restoration

The field of image restoration (sometimes referred to as image de-blurring or image de-convolution) is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one.

Actually, it tries to perform an operation on the image that is the inverse of the imperfections in image formation system. In the use of image restoration techniques, the features of the degrading system and the noise are assumed to be known a priori. In practical situations, one might not be able to get this information directly from image formation process. The aim of blur identification is to estimate the attributes of the imperfect imaging system from the observed degraded image itself before to the restoration process. The combination of image restoration and blur identification is often referred to as blind image de-convolution [3].

III. ANALYSIS ON BLIND IMAGE DE-CONVOLUTION

Blind de-convolution is usually the problem of recovering a sharp version of an input blurry image when the blur kernel is unknown [2]. By decomposing a blurred image y it can be represented as

y = k !x

Where

x is a visually plausible sharp image, and

k is a non-negative blur kernel.

De-convolution is a longstanding issue in many areas of signal and image processing (e.g., biomedical imaging astronomy, remote-sensing). For instance, research in astronomical image de-convolution has recently seen considerable work, partly triggered by the Hubble space telescope (HST) optical aberration problem at the beginning of its mission. In biomedical imaging, researchers are also increasingly depending on de-convolution to enhance the quality of images obtained by confocal microscopes [4]. De-convolution might then prove crucial for exploiting images and extracting scientific content.

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IV. RELATED WORK ON BLIND IMAGE DECONVOLUTION ALGORITHMS

There are different types of filtering methods available to decrease noise and blurring, but each has its own disadvantages, hence various de-convolution algorithms were developed.

D. A. Fish et. al have developed a blind de-convolution algorithm based on the Richardson–Lucy de-convolution algorithm. It's developed from Baye's theorem. It's been widely used in many applications as it is adapted to Poisson noise. In this algorithm initial guess is needed for the object to start algorithm. Then, in subsequent iteration large deviation in the guess from true object are lost rapidly in initial iteration while detail is added more slowly in subsequent iteration. Two iterations are done within blind iteration, one for object evaluation and other for PSF evaluation [1]. Benefits of this algorithm include a nonnegative constraint if the initial guess f0(x) H0 in which energy is conserved as the iteration proceeds.

Jae Myung have projected maximum likelihood estimation approach, that is actually developed by R.A. Fisher in 1920, specifies that desired probability distribution makes the observed data most likely[6]. Estimation of parameter is made so that the probability of receiving the observed image given the parameter set is maximized. Advantage of this method is to estimate true image produced at each iteration and algorithm is terminated when result is obtained [7].

M. Mattavelliet. al have proposed Kalman filtering method for image restoration where a degraded image is split into tuned channels that give set of sub images. Each perceptual component represent original image within band of frequency. It needs2 models. Observation model that link original image to the corrupted one and image model give relation between currently processed pixel and those already restored. Restoration is acquired by recombining all restoration components. Benefit of this method is avoiding serious process load [8].

S. DerinBabacanprojected an algorithm for total variation (TV) based blind de-convolution and parameter estimation using variational framework. In this, blind de-convolution method is performed where unknown image, blur, and hyper parameters are estimated at the same time. Unknown parameters may be of Bayesian formulation can be calculated automatically using only observation or also by using prior knowledge with different confidence values to enhance performance of algorithm. It offers higher quality restoration in both synthetic and real image experiment [3].

Feng-qing Qin has presented the technique of blind image super-resolution reconstruction. The point spread function of imaging system is estimated to approximate the low resolution imaging process far more accurately. Using Wiener filtering image restoration algorithm multiple error parameter curves are generated at different parameters. The super resolution reconstructed image has higher spatial resolution and better visual effect [5].

V. POINT SPREAD FUNCTION (PSF)

Most blurring processes can be approximated by convolution integrals, also called as Fredholm integral equations. The blurring is characterized by a Point-Spread Function (PSF) or impulse response. PSF is the result of the imaging system for an input point source. All the blurring processes in this paper are linear and have a spatially invariant PSF [10].

For discrete image processing, the convolution integral is replaced by a sum. The blurry image x(n, m) is acquired from original image s(n, m) by this convolution:

$$x\,(n,m) = \sum_{a=-\infty}^{+\infty} \sum_{b=-\infty}^{+\infty} s(n+a, m+b) \quad (1)$$

The function h(n, m) is the discrete Point Spread Function for the imaging system. Also of interest is Discrete Fourier Transform (DFT) representation of the point-spread function, given by:

$$H\,(u,v) = \sum_{n=0}^{n-1} \sum_{M=0}^{M-1} h(n,m) \quad (2)$$

H(u, v) gives a set of coefficients for plane waves of different frequencies and orientations. These plane waves, termed as spatial frequency components, reconstruct the PSF exactly when multiplied by the coefficients H(u, v) and summed. The function H(u, v) is referred to as the transfer function, or system frequency response. By examining |H(u, v)|, one can immediately determine which spatial frequency components are passed by the imaging system.

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Figure 3. Top row contains estimated PSFs: the blur develops along trajectory

5.1 PSF GENERATION

The PSFs constituting the collections HTthat are accustomed to compute the restoration-error models, are acquired by sampling continuous trajectories on a (regular) pixel grid. Every trajectory contains of the positions of a particle following a 2-D random motion in continuous domain. The particle has an initial velocity vector with each iteration is affected by a Gaussian perturbation and by a deterministic inertial component, directed toward the present particle position. In addition, with a small probability, an impulsive perturbation aiming at inverting the particle velocity arises, mimicking a sudden movement that occurs when the user presses the camera button or tries to compensate camera shakes.

At every step, velocity is normalized to ensure that trajectories corresponding to equal exposures have the same length. Each perturbation (Gaussian, inertial, and impulsive) is ruled by its own parameter, and each set HT contains PSFs sampled from trajectories produced by parameters spanning a meaningful range of values. Rectilinear trajectories are generated when all the perturbation parameters are zero.

Each PSF hT∈ HT contains in discrete values that are calculated by sampling a trajectory on a regular pixel grid, using sub-pixel linear interpolation. Collections corresponding to different exposure times are acquired by scaling the values of each PSF by a constant factor.

Remember that Image restoration refers to removal or minimization of known degradations in an image. It includes de-blurring of images degraded by the restrictions of the sensor or its environment, noise filtering, and correction of geometric distortions or non-linearity due to sensors. It explains the imaging system response to a point input, and is analogous to the impulse response. A point input, represented as a single pixel in the "ideal" image, will be reproduced as something other than a single pixel in the "real" image.

"Point Spread Functions" explain the two-dimensional distribution of light in the telescope focal plane for astronomical point sources. Modern optical designers put a great deal of effort into minimizing the size of the PSF for large telescopes.

Good PSF evaluation is especially critical for telescopes that are meant to have near-diffraction limited performance. That obviously includes space telescopes. But it also includes large ground-based telescopes that are equipped with "active" or "adaptive" optics systems, which can greatly reduce the effects of atmospheric seeing on the PSF.

VI. CONCLUSION

Restoration technology of image is one among the vital technical areas in image processing. In this paper various blind image restoration methods have been discussed. These methods are based on blind de-convolution approach with partial information available about true image. Benefit of using blind de-convolution algorithm based on Richardson–Lucy de-convolution algorithm is to de-blur the degraded image with prior knowledge of PSF and Poisson noise whereas other algorithms focus on the Gaussian noise. Better restoration can be achieved by estimating the PSF, as this approach doesn't require verification of the blur kernel against the blurred image, the de-blurring can be performed quickly enough for interactive use.

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