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A Study on Image Restoration and Deconvolution Techniques

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***Abstract*— -** Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise and camera misfocus. Deconvolution is an example of image restoration method. The deconvolution tries to invert the blurring of an image that is modeled by the convolution g = f*h+n. Blind deconvolution tries to do this without knowledge of the point spread function h that blurred the image. In this paper, different methods for image restoration viz. Deterministic Filter, Bayesian Estimation and iterative distribution reweighting (IDR) are discussed in detail.

***Keywords*—** Bayesian estimation, blind image deconvolution, Maximum A Posteriori (MAP) estimation, L1-Regularization, Iterative Distribution Reweighting (IDR).

I. INTRODUCTION

Images area unit made to record or show helpful data. owing to imperfections within the imaging and capturing method, however, the recorded image invariably represents a degraded version of the initial scene. The undoing of those imperfections is crucial to several of the next image process tasks. There exists a large vary of various degradations that require to be taken into consideration, covering for example noise, geometrical degradations (pin cushion distortion), illumination and color imperfections (under/over-exposure, saturation), and blur. This paper concentrates on basic ways for removing blur from recorded sampled (spatially discrete) pictures.

Blurring could be a kind of information measure reduction of a perfect image thanks to the imperfect image formation method. It are often caused by: Relative motion between the camera and also the original scene or by AN optical system that's out of focus. once aerial pictures ar created for remote sensing functions, blurs ar introduced by region turbulence, aberrations within the optical system, and relative motion between the camera and also the ground. lepton micrographs arcorrupted by spherical aberrations of the lepton lenses, and CT scans suffer from X-ray scatter.

In addition to those blurring effects, noise continuously corrupts any recorded image. Noise could also be introduced by the medium through that the image is made (random absorption or scatter effects), by the recording medium (sensor noise), by measuring errors owing to the restricted accuracy of the sound system, and by quantisation of the information for digital storage.

The loss of information due to degradation could be devastating in numerous fields like optics, medical, astronomy, to name a few. The degradation of images is no small problem considering the enormous expense in acquiring the images in the first place. Thus arises the need for restoration of blurred/degraded images.

II. IMAGE RESTORATION

The field of image restoration is usually stated as image deblurring or image deconvolution. it's involved with the reconstruction or estimation of the uncorrupted image from a blurred and howling one. basically, it tries to perform AN operation on the image that's the inverse of the imperfections within the image formation system.

In the use of image restoration ways, the characteristics of the degrading system and therefore the noise ar assumed to be known a priori. In sensible things, however, one might not be ready to get this info directly from the image formation method. The goal of blur identification is to estimate the attributes of the imperfect imaging system from the discovered degraded image itself before the restoration method. the mixture of image restoration and blur identification is commonly observed as blind image deconvolution. Types of Image Restoration, based on the availability of Blurring PSF, there are two categories of image deconvolution problems: Non blind Deconvolution and Blind Deconvolution

A. *Non Blind Deconvolution*

If the blur kernel is given as a prior, recovering the original image becomes a Nonblind Deconvolution problem.

III. BLUR PROCESS

If we denote $f(n1,n2)$ the desired ideal spatially discrete image that does not contain any blur or noise, then the recorded image $g(n1,n2)$ is modeled as:

$$g(n1, n2) = d(n1, n2) * f(n1, n2) + w(n1,n2)$$

$$= \sum_{k1=0}^{N-1} \sum_{k2=0}^{M-1} d(k1,k2)\, f(n1-k1, n2-k2) + w(n1, n2)$$

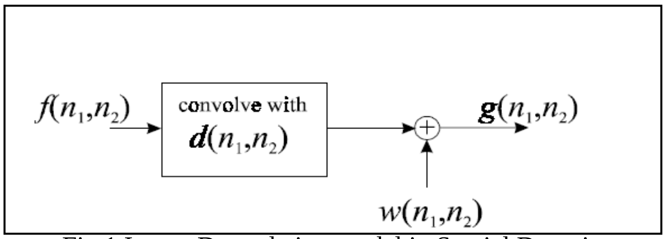

Fig.1 Image Degradation model in Spatial Domain

f(n1,n2)- Original

Image g(n1,n2)-

corrupted image

d(n1,n2)- convolution kernel or point-spread

function w(n1,n2) - noise that corrupts the blurred

image

An alternative manner of describing blurring is thru its spectral equivalence. By applying distinct Fourier transforms, we tend to get the subsequent illustration

$$G(u, v) = D(u, v)F(u, v) + W(u, v)$$

where (u,v) are the spatial frequency coordinates, and capitals represent Fourier transforms.

A. Spatially invariant blurs

Point-spread performs thought of during this paper don't seem to be a function of the spatial location into account, i.e., they're spatially invariant. basically this suggests that the image is blurred in barely an equivalent approach at each spatial location.

B. Spatially varying blurs

Point-spread functions that do not follow this assumption are, for instance, due to rotational blurs (turning wheels) or local blurs (a person out of focus while the background is in focus). The modeling, restoration and identification of images degraded by spatially varying blurs is still a largely unsolved problem.

B. *Blind Deconvolution*

If the blur kernel is also unknown, how to reverse the effect of convolution on the blurred image is then a Blind Deconvolution problem

The deterministic filter can be modeled as deterministic function of the input blurred image, by denoting the output sharp image. One of the most well-known approaches in this paradigm is unsharp masking, of which the basic idea is to reduce the low frequency first, and then highlight the high-frequency components. The performance varies according to the adopted high-pass filters and the adaptive edge weights. This approach assumes that the blurred edges do not drift too far away from the latent sharp edges; thus, it can handle only the defocus blurs and very small motion blurs. For very large blurs, the image narrow edges or details are severely damaged and very difficult to restore.

A practical solution is to detect and restore large step edges explicitly or implicitly, which we call the step-edge-based filter (SEBF). Explicit SEBF first locates the step edge and then propagates the local intensity extrema toward the edge. Implicit SEBF performs edge detection and restoration in a single step, based on zero crossings of high-pass filters. Commonly used implicit SEBFs include the shock filter, the backward diffusion,

IV. APPROACHES IN IMAGE RESTORATION

Chao Wang et al[1] compares two approaches of image restoration: Deterministic Filter, Bayesian Estimation.

the morphological filtering, the fuzzy operator, and many other adapted versions.

The SEBF has the following advantages:

- The SEBF can handle various blurs without adaptation because it is independent of the blurring processes (blur models), and
- The performance of the SEBF is not constrained by the sample number (SN) because it depends on image local features rather than sufficient samples.

Disadvantages:

- Implicit SEBF is very sensitive to image noise
- The results for very large blurs are still unreliable.
- SEBF cannot restore the narrow edges whose scales are smaller than the blur kernel. Therefore, it cannot give accurate results for the images containing many narrow edges.

Bayesian Estimation, Both the kernel and image are taken as samples from some probability spaces. The goal is to solve for the unknowns that minimize the expected value of a loss function. The most commonly used loss function is the Dirac delta function, which yields the maximum a posterior (MAP) estimator.

Advantages:

- The approach is not sensitive to local narrow edges because it depends on statistics
- Performance highly depends on the SNs and statistics.

Charu Khare et al[4] has used Artificial Neural Network (ANN) for restoring images. ANN provides a robust tool for approximating a target function given a set input output example and for the reconstruction function from a class of images. Algorithm such as 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. The Back propagation neural network approach for image restoration is capable of learning complex non-linear functions is expected to produce better structure especially in high frequency regions of the image.

Laura B. Montefusco et al[10] thought-about the L1-regularized image deblurring drawback and evaluated its resolution victimisation the reiterative forward–backward cacophonous methodology. The approach projected a replacement adaptive rule for the estimation of the regularization parameter that, at every iteration, dynamically updates the parameter price, following the evolution of the target purposeful. The reiterative algorithmic rule mechanically stops, while not requiring any assumption concerning the perturbation method, once the parameter has reached a on the face of it close to best price. The projected rule yields restoration results competitive with those of the most effective progressive algorithms.

Another approach described by Taeg Sang Cho et al[3] brings forth limitation of MAP estimator. A MAP estimator, when used with a sparse gradient image prior, reconstructs piecewise smooth images and typically removes textures that are important for visual realism. The approach presents an alternative deconvolution method called iterative distribution reweighting (IDR) which imposes a global constraint on gradients so that a reconstructed image should have a gradient distribution similar to a reference distribution. The algorithm is able to restore rich mid-frequency textures. It improves the visual realism of reconstructed images compared to those of MAP estimators.

IDR defines a cumulative penalty function that gradually pushes the parameterized empirical distribution toward the desired distribution which results in an image with a gradient distribution that closely matches that of the desired distribution.

- It is not sensitive to image noise if the noise is not too much to change the statistics.

Disadvantages:

- Bayesian estimator is built for a specific blur model and cannot handle other types of blurs without adaptation

A vital drawback during this approach is deciding the specified gradient distribution. To do this, it takes advantage of the very fact that a lot of textures area unit scale invariant. Gradient profiles area unit roughly equal across scales. the method involves deconvolving a picture, followed by downsampling. The downsampled image is then accustomed estimate the gradient distribution. The result's the dimensions invariant gradient distribution is maintained, whereas the noise introduced by deconvolution is reduced throughout downsampling. once deconvolving the degraded image, a MAP figurer is employed with a selected image previous, tuned to revive completely different textures moderately well at the expense of a rather clamant image reconstruction (i.e., a comparatively little gradient penalty). A desired distribution is computed employing a downsampled version of the image over a collection of segments.

Disadvantages:

Since the approach synthesizes textures or gradients to match the desired distribution, the peak signal-to-noise ratio (PSNR) may be below other techniques.

However, the results are generally more visually pleasing and it improves perceived quality of reconstructed image. But lower PSNR suggests there is room for improvement.

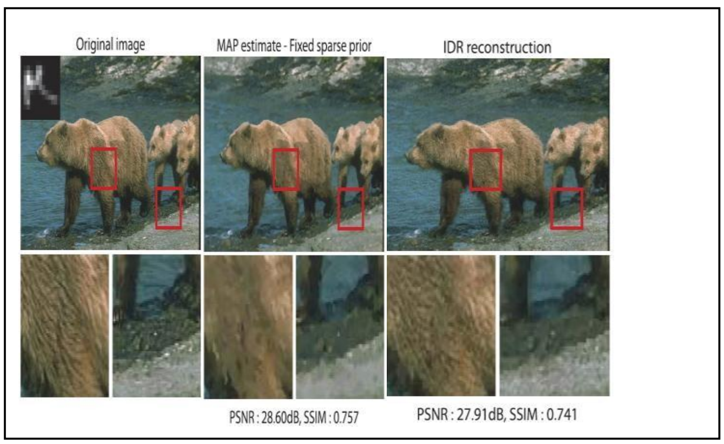

Fig 2. Comparison of the performance of IDR against MAP estimator with sparse gradient prior. The red boxes indicate the cropped regions. Although the PSNR and the SSIM of IDR results are often lower than those using MAP estimators, IDR restores more visually pleasing textures (see bear furs).

V. CONCLUSION

Various practical problems lead to the necessity of digital processing of blurred, distorted images. The distortions may be caused by the relative motion of the camera and the object, the turbulence of the medium, and the imperfectness of detecting equipment. As a rule, the problem of restoring a distorted image is formulated as an inverse problem of mathematical physics.

The possibility of applying various mathematical methods to solve problems of image restoration has been actively studied during the last decade. It should be noted that restoring algorithms are based on various models of image and noise.

The main requirement for all restoration models is the uniqueness of the solution and its stability against errors in the input data. As for any inverse problem with incomplete data, the result of restoring a distorted image is always reduced to a

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