An Extensive Literature Review on Digital Image Restoration

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Abstract- In this review paper Image Restoration process has been analyzed for reconstructing or recovering an image that has been degraded by some degradation phenomenon. Restoration techniques are primarily modeling of the degradation and applying the inverse process in order to recover the original image. Image restoration techniques exist both in spatial and frequency domain. Due to imperfections in the image formation process and the imaging device, the observed image often represents the degraded version of the original image. The corrections of these imperfections are mandatory in many of the subsequent image processing and vision tasks. Different types of degradations exist in the nature which includes noise, blur, geometrical degradations, illuminations etc. In this research work, an analysis has been made on removing the blur and noise from degraded images. Due to enormous applications of image restoration, researchers have gained interest to work in this area.

Keywords- Image deblurring, Image restoration.

I. INTRODUCTION

The research on image restoration started in 1950s with astronomical imaging when scientists of United States of America and Soviet Union were involved in producing images of the Earth and the solar system. The images were degraded versions of the original images due to substandard imaging environment, spinning and the tumbling of the space craft. To retrieve the meaningful information from the degraded images, image restoration techniques were used. It is not a surprise to see that digital image restoration is used in astronomical imaging even today. Ground based imaging systems were also subject to blurring due to change in refractive index of the atmosphere. Image restoration also plays an important role in medical imaging. It has been used to remove film-grain noise in X-ray images, angiography images and additive noise in magnetic resonance images. It has applications to quantitative auto radiography (QAR) in which image is obtained by exposing X-ray film to a

Model of Image Degradation

An image may be described as a two-dimensional function I

$$I = f(x;\ y)$$

where x and y are spatial coordinates. Amplitude of f at any pair of coordinates (x; y) is called intensity I or gray value of the image. When spatial coordinates and amplitude values are all discrete quantities, the image is called digital image. If f(x; y) is the original image, h(x; y) is a degradation function and ´(x; y) is the additive noise then the degraded image g(x; y) is given as [9]:

$$g(x;\ y) = f(x;\ y)¤h(x;\ y) + ´(x;\ y)$$

where the symbol ¤ indicates spatial convolution. Since convolution in spatial domain is equal to multiplication in the frequency domain, the corresponding frequency domain representation is given as:

$$G(u;\ v) = F(u;\ v)H(u;\ v) + N(u;\ v)$$

where the terms in capital letters are the Fourier transforms of the corresponding terms in equation.

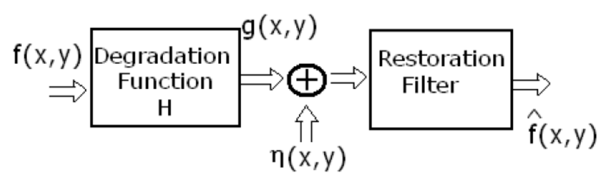

Fig. 1 Model for Image Degradation/Restoration Process.

Many types of the degradations can be approximated by linear, position invariant processes. Since degradations are modeled as being the result of convolution, and restoration seeks that apply the process in reverse, the term image deconvolution issued to signify linear image restoration.

Point Spread Function

The linear position-invariant function h(x; y) in above equation is known as a point spread function. The point spread function gets convolved with the original image to give the degraded image. Some commonly occurring image degradations, which are linear and position-invariant are given below.

Motion Blur often it may be seen images blurred because of camera movement during image capture. Suppose the relative motion is of velocity at an angle µ with the horizontal axis and if T is the duration of exposure, then the blur length is L = ºT and the motion blur PSF can be expressed as

$$h(x,y) = \begin{cases} \frac{1}{L} & if\ \ 0 \le |x| \ \le L\,cos;\ \ y = Lsin \\ 0 & Otherwise \end{cases}$$

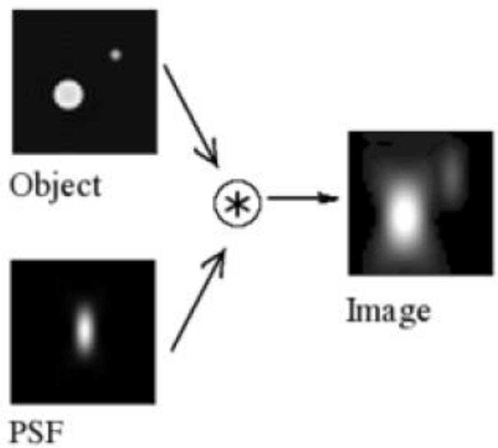

Fig. 2: Convolution of the point spread function with a point object gives the ob-served image.

Camera Defocus

Another commonly occurring blur is because of improperly focused camera. Assuming the lens system is of circular aperture, with radius r the point spread function can be expressed as

$$h(x,y) = \begin{cases} 0 & if\ \sqrt{x^2+y^2}\ \ > r \\ \frac{1}{\pi r^2} & Otherwise \end{cases}$$

Denoising Techniques

When the only degradation present in an image is noise, then equation (1.2) becomes

$$g(x;\ y)\ =\ f(x;\ y)\ +\ ´(x;\ y)$$

and Equation becomes

$$G(u;\ v)\ =\ F(u;\ v)\ +\ N(u;\ v)$$

Denoising techniques exist in both spatial domain as well as frequency domain.

Spatial filtering is preferred when only additive noise is present. The different classes [9] of filtering techniques exist in spatial domain filtering.

- Mean filters
- Order-Statistics filters
- Adaptive Filters

Arithmetic mean filter

This belongs to the category of mean filters. In this method the middle pixel value of the filter window is replaced with the arithmetic mean of all the pixel values within the filter window. A mean filter simply smoothes local variations in an image. Noise is reduced as a result of this smoothening, but edges within the image get blurred.

Median filter

Median filter comes under the class of order-statistics filters. Response of Order-statistics filters is based on ordering the pixels contained in the filter window. Median filter replaces the value of a pixel by the median of the gray levels within the filter window. Median filters are particularly exceptive in the presence of impulse noise.

Adaptive Filters

Adaptive filters change its behavior based on the statistical characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. But the improved performance is at the cost of added filter complexity Mean and variance are two important statistical measures using which adaptive filters can be designed. For example if the local variance is high compared to the overall image variance, the filter should return a value close to the present value. Because high variance is usually associated with edges and edges should be preserved.

Frequency Domain Filtering

The frequency domain is an alternate way to represent an image. It deals with the frequency of the gray levels of the pixels in the image i.e. the variation in the gray level. Considering the frequency components of an image can provide an insight and rationale for certain filtering and processing operations. In frequency domain filtering the image is mapped from spatial domain to frequency domain by taking Fourier transform of the image. After mapping filtering operation is done on the image (like low pass and high pass filtering etc). After doing the filtering operation the image is remapped to spatial domain by inverse Fourier transform to obtain the restored image

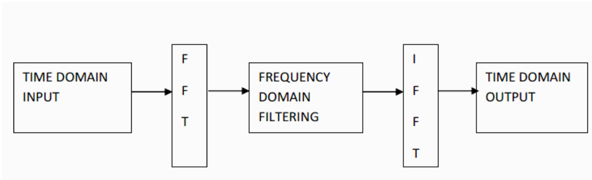

Fig. 3: Frequency domain filtering model.

II. SYSTEM MODEL

Image Degradation Model

The degraded image $g(x, y)$ is obtained by applying the degradation operator H onto the image $f(x, y)$ along with the additive noise $\eta(x, y)$. The degradation phenomenon is mathematically expressed as,

$$G(x,y) = H[f(x,y)] + \eta(x,y)$$

The objective of image restoration is to estimate $f(x, y)$ from the observed image $g(x, y)$ using the known value of H [7,8]. The overall degradation and restoration model is shown in the Fig. 4. The operator H may be linear or nonlinear.

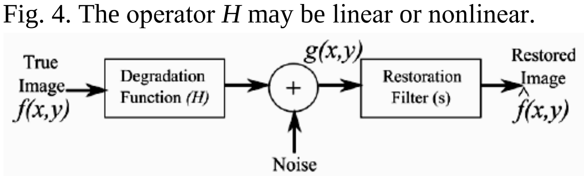

Fig. 4: Image degradation restoration model.

Mostly, it is assumed to be linear which satisfies the principles of superposition and homogeneity [6].

III. LITERATURE REVIEW

In the year of 2014 Jian Zhang; Debin Zhao; Ruiqin Xiong; Siwei Ma; Wen Gao,[1] presented a high-fidelity image restoration by characterizing both local smoothness and nonlocal self-similarity of natural images in a unified statistical manner. The main contributions are three-fold. First, from the perspective of image statistics, a joint statistical modeling (JSM) in an adaptive hybrid space-transform domain is established, which offers a powerful mechanism of combining local smoothness and nonlocal self-similarity simultaneously to ensure a more reliable and robust estimation. Second, a new form of minimization functional for solving the image inverse problem is formulated using JSM under a regularization-based framework. Finally, in order to make JSM tractable and robust, a new Split Bregman-based algorithm is developed to efficiently solve the above severely underdetermined inverse problem associated with theoretical proof of convergence. Extensive experiments on image in painting, image deblurring, and mixed Gaussian plus salt-and-pepper noise removal applications verify the effectiveness of the proposed algorithm.

In the year of 2013 Boujena, S.; El Guarmah, E.M.; Gouasnouane, O.; Pousin, J. [2] investigated image restoration, the denoising is an important step. Several models of non-linear diffusive filters requiring solving partial differential equations have been proposed in the literature [2] during the last decades. The existence and uniqueness of a solution in Hilbert space has been established under suitable conditions on the filtering function for the Perona Malik model [5] considering Dirichlet homogeneous and inhomogeneous boundary conditions [2]. In this work, authors proposed a nonlinear diffusion model inspired by the Perona-Malik one taking into account the Neumann boundary condition. The existence, uniqueness and regularity of the solution to the mathematical problem are established in a Hilbert space. The numerical simulation of the discretized problem is performed using the finite elements method. The effectiveness of this model has been tested on many noisy images with noises of different natures. A comparison of signal to noise ratio (SNR) is used to estimate the quality of the restored images by this model and the Perona-Malik one.

In the year of 2013 Ogawa, T.; Haseyama, M., [3] described to a kernel cross-modal factor analysis (KCFA) based missing area restoration method including a new priority estimation scheme is presented in this paper. The proposed method estimates latent relationship between missing areas and their neighboring areas by deriving projection matrices minimizing their errors in the latent space based on KCFA. Experimental results show subjective and quantitative improvements of the proposed method over previously reported restoration methods.

In the year of 2013 Pavlikov, V.V.,[4] has presented Radiometric devices and systems widely apply at the solution of problems of radio astronomy, radio meteorology, remote sensing, radar-location and medicine. In such systems power characteristics of radiation of physical objects are subject to estimation. For restoration of radiometric images (power characteristics as functions of angular or spatial coordinates) use two main approaches. The first is based on use of scanning or mobile radiometers. Though the analysis showed that, paying essential attention to a choice of geometry of antenna arrays, questions of synthesis optimum algorithms of space-time signal processing in such systems need detailed research.

In the year of 2013 Lin Zhong; Sunghyun Cho; Metaxas, D.;

Paris, S.; Jue Wang,[5] worked on a new method for handling noise in blind image deconvolution based on new theoretical and practical insights. Author's key observation is that applying a directional low-pass filter to the input image greatly reduces the noise level, while preserving the blur information in the orthogonal direction to the filter. Based on this observation, author's method applies a series of directional filters at different orientations to the input image, and estimates an accurate Radon transform of the blur kernel from each filtered image. Authors reconstruct the blur kernel using inverse Radon transform. Experimental results on synthetic and real data show that author's algorithm achieves higher quality results than previous approaches on blurry and noisy images.

In the year of 2013 Dali Liu; Lirong Qiu; Weiqian Zhao [6] presented a novel micro-Nano measurement method using confocal microscopy with super-resolution image restoration is proposed to achieve the measurement of all of the lateral dimensions of the line width step sample including the dimension that is smaller than the diffraction limit. In this method, first, the step is over-sampling scanned to obtain the intensity image data at focal plane; and then using the respective restoration to obtain super-resolution restoration images of the flat region and the bevel region; finally, the ideal profile is estimated from the restoration images and used to locate the edges of the structures to measure. The method reaches an average measurement value of 0.162μm for the bevel edge, and it is 0.015μm smaller than that measured by AFM.

IV. PROBLEM IDENTIFICATION

Image blurring is a common phenomenon that exists in various applications like photography, remote sensing, medical imaging, etc. The degradation may occur due to camera misfocusing, atmospheric turbulence, relative object-camera motion and various other reasons. For the last few decades, researchers are working in the field of image restoration. The problem is still open due to its ill-posed nature and requires significant research. The Iterative Blind deconvolution scheme shows some promise, even though quality of the restored image is not satisfactory. The main limitation of IBD is its slow convergence rate. The convergence can be accelerated by limiting the high magnitude values in the frequency domain of estimated image as well as the estimated PSF.

V. CONCLUSIONS AND FUTURE SCOPE

Image enhancement techniques deal with improving the visual appearance of the image so that it will be more pleasing to the human eye. Some of the examples of image enhancement are histogram equalization, Unsharp masking, contrast stretching, etc. On the other hand, *image restoration* accentuates on retracing the original image as close as possible from the degraded observation. The restoration techniques assume a degradation model and design a filter to achieve an approximated version of the original image. The closeness of the restored image towards the true image depends on the accuracy of the model and the designed filter. Both enhancement and restoration techniques may improve the appearance of the image using a filter. Though, enhancement is more subjective in nature and depends on individual's perception.

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