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REVIEW ARTICLE

Review of Linear Image Degradation and Image Restoration Technique

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ABSTRACT

The field of image restoration, image deblurring, or image deconvolution concerns with an estimation of the uncorrupted image from degraded one. The restoration of the image is classified into the degradation phase and the restoration phase. This paper shows a review to the degradation blurring functions and noise functions types as well as the classification of restoration methods for linear reconstruction technique, which divided to non-blind methods and blind methods, constrained image restoration and un-constrained image restoration and the constrained classifies into non- iterative and iterative methods.

Key words: Blurring, constrained, deconvolution, degradation, iterative, noise, restoration

INTRODUCTION

Image restoration mentions as removal or minimizing of noted degradations in a picture. Which concerns with de blurring of image destoration which defected by optical system, or environment, correction of degradation by noise filtering.[1,2] Image restoration has two techniques kinds: Spatial-domain techniques and frequency-domain techniques. The field of image restoration, image deblurring, or image deconvolution concerns with an estimation of the uncorrupted image from degraded one. The restoration of the image is classified into the degradation phase and the restoration phase.[3]

The degradation phase is concerned with the real image that degraded by the blurring and the extra noise. The resultant image of this part is called the degraded image. Whereas, the restoration phase is concerned with using many filters on degraded image and estimating a picture for the original image to be produced as an output. Whereas, the image restoration methods is classified into blind class and non-blind class.[4-6]

Blind technique of restoration which the blurring operator is unknown. Primary knowledge of the function h(x, y) not necessary but the blurring function estimation is needed to use for de-blurring the distorted image. The non-blind method of restoration which the blurring factor is known a prior knowledge of $h(x, y)$ needed. Remove the blurs from the degraded images be conditioned on the blurring function knowledge.[6,7]

This paper illustrates the mathematical bases of the model of image degradation and restoration, and the classification of degradation and restorations is also mentioned with mathematical details.

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MATHEMATICAL MODEL OF DEGRADATION

The degradation model results from the blurring function and the effect of noise function. The model which presents the degradation process in spatial domain is:[8]

$$g(x,y)=h(x,y)\circledast f(x,y)+n(x,y) \qquad (1)$$

Where g(x,y) presents the degraded version of image, f(x,y) presents the original version of the image, n(x,y) presents the additive noise function, and h(x,y) presents the blaring function, and the model which presents the degradation process in the frequency domain is:[8,9]

$$G(u,v)= H(u,v)\bullet F(u,v)+ N(u,v) \qquad (2)$$

For: u, v = 0, 1, 2, 3, 4…, N-1, and (u,v) represents a spatial frequency coordinates, G(u,v,) H(u,v), F(u,v), and N(u,v), are the Fourier transform for g(x,y), h(x,y), f(x,y), and n(x,y), respectively. The convolution in the spatial domain is equal to the multiplication operation in the frequency domain or Fourier domain, and in this restoration model, the real image and the noise combined linearly so that the problem of restoring the real image from the distorted image is defined as a linear image restoration problem.

PRIORI KNOWLEDGE OF DEGRADATION SOURCES

A picture sometimes comes as a signal carrying data about physical target which is not noticeable directly. In general, the data consist of a degraded illustration of the source object. One will distinguish two sources of degradation: The process (or method) of image formation and image recording way. The degradation produced from image formation refers to blurring, while the degradation caused by the recording tools refers to noise.[10] The information regarding the imaging system and the visual image perception helps in generating the noise model and estimating of the statistical characteristics of noise embedded in a picture required because it assists in separating the noise signals. More explanations about the two types of degradation are given in the following subsections.

BLURRING BASED DEGRADATION

The diffraction limitation is resulting an image of a point target. It is a patch of light intensity known as the point spread function (PSF).[11] PSF acts the energy distributed on the image plane due to point source on object plane.[12] PSF known as a two-dimension impulse response came from a point source of light pass through the degradation system with the absence of noise.[13] The blurring model is given as:[8]

$$g_b(x,y)=h(x,y)f(x,y) \tag{3}$$

Which is a convolution between PSF and object.[14-16] .The PSF cab is space invariant (SIPSF) or space variant function (SVPSF). The SIPSF changes only in the inputs position, however clearly changes the output placement with keeping similar perform, this characteristic look within the linear systems, not rely on pixel location, and the PSF is the same for all pixels in a picture.[17] Whereas, the SVPSF changes shape and position, the PSF depends on the location of the object, this is property related to non-linear system, and the PSF changes throughout the image.[17] In general, the blur sorts can be classified conjointly as follows:[18]

Liner motion blurs

The relative motion gives a blurring result throughout exposure between the camera and the object. Suppose $f^{(0)}$ (m) illuminances from target, which might result in the image plane of camera within non-existence of relative motion in between the camera device and real object. The blurring is space-invariant solely within the case where the target and image planes area unit parallel, and also the motion is translation. If we tend to assume that these conditions are applied, then the translation motion is delineate by a time-dependent vector:[9,10]

$$Y(t)=\{Y_1\ (t).Y_2(t)\}0\leq t\leq T \tag{4}$$

Where Y1 and Y2 are time-dependent vectors and T is the exposure interval.
This vector defines the trail, with regard to a fixed coordinated system within the image plane that is determined by the origin of a coordinated mounted with regard to the moving target. One can assume that, at time equal to 0, the origins of two systems coincide. Then, the flight delineates by an arbitrary point of the moving target is given by +Y(t), in order that, if m may be a given point within the mounted fixed image plane, this point is reached at time t, by the point of moving target that, at time equal to zero, is given by Y'=m−Y(t). if clear image which is free from noise "g^0 (m)" in the point m is the results of the addition of all the points contribution Y' = m−Y (t) which Passing during m in the interval [0, T].[10]

$$g^0(m)=\frac{1}{T}\int_0^T f^0\left[m-Y(t)\right]dt \tag{5}$$

The factor (1/T) is introduced as a normalization factor.

Optical system defects

The environment through that the waves should transmit while crossing from the object to the picturing system is oneself optically imperfectness. the particular resolution that a distant from than the theoretical optical phenomenon limits that acquired by Rayleigh criterion is:[18]

$$\Delta\alpha = 1.22\frac{\lambda}{D_a} \tag{6}$$

Where Δa is resolving power and λ is the lights wavelength; D_a is the lens apertures diameter. Another defect of optical system is aberration. One of the aberration types is out-of focus, within the case of a lens, associate point of target is focused. If the distance from the lens, d_0 satisfies the lens conjugation law:[10]

$$\frac{1}{d_0} + \frac{1}{d_i} = \frac{1}{d_f} \tag{7}$$

Wherever d_i presents the distance in between the lens and the images plane, and d_f is the focal length of lens. If condition of Eq. (6) is not satisfied, then the image of the point, forever in line with geometrical optics, is a disc, also known as The Circle of Confusion (COC). The radius of COC may depend on the wavelength through the refractive index of the lens. Finally, as issues the intensity distribution among the COC, it follows from geometrical optics that it is around uniform over COC so the image of an out-of focus point, situated on the optical axis, is given by:

$$\mathrm{H}(x) = \frac{1}{\pi R^2 COC} X_{COC}(X) \tag{8}$$

Where H(x) is PSF, R_{COC} is the radius of COC, and X_{COC} is the characteristic function of the COC.

Inhomogeneous optical media

Atmospheric district turbulence is due to irregular variation within the index of the refraction of the medium between the objectives and imaging system and denotes that the wavefront transmission of point source origin through a tumultuous medium, for example, the planet atmosphere causes turbulence in phase and degrades the quality of the created image. The blur described by Gaussian function is given as: [19]

$$H(x,y) = \frac{1}{\sqrt{2\pi\sigma_b}} e^{-\left(x^2+y^2\right)/2\sigma^2} \tag{9}$$

Where σ_b is the standers deviation of Gaussian function. Although, the blurring come from region turbulence depending on considerable operators such as the time of exposure, temperature and wind speed.[20,21]

NOISE-BASED DEGRADATION

The noise installed in a picture in many sorts. The noise partitioned into two sorts: Correlated noise or uncorrelated noise. The noise sorted into signal dependent or signal independent, the information relating to the picturing system and visual perceptiveness of the image is necessary in noise model's creation, and the evaluating of the statistical properties of noise inserted in an image is important to put out the noise from the image signal.[22,23] There are four kinds of noise given in the following subsections:[22,24]

Additive noise

Additive noise is one sort of distortion that appears in the degraded image, formed by the dispersion among the atmosphere, due to the scattering of electromagnetic waves through distinct directions also because of the minutes of mud and impurities presence with small diameters among the air and picturing system inflicting a block light-weight of sunshine in a section at the picture with an increasing in light in disparate areas. The additive noise model format is: [5,25]

$$g_n(x,y)=f(x,y)+n(x,y) \tag{10}$$

Where $g_n(x,y)$ represents the noisy image. Sometimes, the noises generated from sensors are white Gaussian which is additive and signal independent.[24,26,27].

$$n_G(b,s) = \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-(b^2+s^2)/2\sigma^2} \tag{11}$$

Where $n_G(b,s)$ is the Gaussian noise, b is the distance between the center and the vertical axis, s is the distance between the center and the horizontal axis, and σ_n represents the standard deviation of the Gaussian noise.

Multiplicative noise

The granularity noise that came from photographic plates and the spots noise that came from imaging system such as ultrasound imaging are multiplicative in nature, which modeled as:[22,24]

$$g(x,y)=f(x,y)*n_m(x,y) \tag{12}$$

Where $n_m(x,y)$ represents the multiplicative noise.

Impulse noise

Often the sensors generate a high noise pulsed. In general, the noise is generated from a digital or analog image transmission system, which is impulsive in nature,[22,5] this also named data drop noise because statistically its drop the original data values. This noise is also known as salt and pepper noise[24,28,29] which presents in the following equation:

$$g7(x,y)=(1-p)(x,y)+pq(x,y) \quad (13)$$

Where q(x,y) impulsive noise and p a binary parameter takes the values of either 0 or 1. Impulse noise is also simply detected from the distorted image due to the distinction anomalies, when the noise impulses found, then replaced by the signal samples.[5,22,24].

Quantization noise

This noise is characterized by the size of signal quantization interval a signal dependent noise, this noise makes image look like artifacts and produce false contours around the target, the quantization noise also take of the image details which appears in low-contrast.[5,22,23]

RESTORATION ALGEBRAIC APPROACH

The algebraic approach is the concept of finding an estimate of original picture, which minimizes a predefined criterion of performance. Due to simplicity. Because of simplicity, the method depends on least-squares criterion function. The well-known restoration methods are due to considering one of the processes either an unconstrained or a constrained process to least-square restoration problem.[8] According to the effect of blurring function (PSF), whether it is space invariant or space variant image, restoration can be classified into linear and non- linear restoration. The linear restoration is associated with space invariant PSF, while the non-linear restoration is associated with space variant PSF. The linear restoration techniques can be categorized into two techniques: Unconstrained linear restoration and constrained linear restoration. Furthermore, the constrained techniques are classified into direct solution (also known as, linear, non-iterative, or one-shot solution) and indirect solution that is known as iterative solution.[18] More details about some related concepts are given in the following subsections:

Unconstrained restoration

Unconstrained restoration is a restoration technique that the procedure of image recovering is not limited by other constraint conditions. This method looks to be easy to fetch the desirable results, but it is not, especially when the noises are taken into account.[30] The degradation model represented as a system of linear equation in operator in the formulation:

$$g=Hf+n \quad (14)$$

Where g, f, and n represent the degraded image or the distorted picture, the original picture, and the noise, respectively. H represents the linear spatially invariant degradation operator formed from the equation (2.14) and the noise term of the degradation model by the formula:[8]

$$n=g-Hf \quad (15)$$

In the case of no attendance for any information about n, a meaningful criterion function is to find an estimate of original image represented by $\hat{f}$ so that H approximates in a least-squares method by assume that the noise norm ||n|| is small as possible, $\hat{f}$ formula is:

$$\|n\|^2 = \| g - Hf \|^2 \quad (16)$$

Where $\hat{f}$ is restored image, and $\hat{f}$ is minimum. By definition of norm||f||,||f||=$\hat{f}$

$\|n\|^2=nn^t$ and likely $\| g - H\hat{f} \|^2 = (g - H\hat{f})(g - H\hat{f})'$ the square norm of n and $(g - H\hat{f})$, respectively, by the Equation (14) that equivalent view this problem as one of minimizing the criterion function

$$j(\hat{f})=\|g-H\hat{f}\|^2 \quad (17)$$

Where J is a criterion function, a said from the requirement that it minimizes

Eq. (16). $\hat{f}$ is not constrained in any way. Minimization of Eq. (16) is straightforward. Simply by differentiate J with respect to $\hat{f}$, and make the outcome equals to zero vector, which is:

$$\frac{\partial j(\hat{f})}{\partial \hat{f}} = 0 \rightarrow -2H^t\left(g - H\hat{f}\right) \quad (18)$$

Where H^t is the transpose of H. Solving Eq. (18) for $\hat{f}$ yields:

$$\hat{f}=(H H^t)^{-1} H^t g \quad (19)$$

By letting M = N so that is squared matrix, and assuming that H^{-1} exists, Eq. (19) reduces to:

$$\hat{f}=H^{-1}\left(H^t\right)^{-1} H^t g = H^{-1} g \quad (20)$$

Frequency-domain representation:

$$\hat{F}(u,v)=\frac{G(u,v)}{H(u,v)} \quad (21)$$

Inverse filter related to unconstrained restoration technique.

Constrained restoration

Let Q be a linear operator for $\hat{f}$ Consider the least-squares restoration problem like one of minimizing functions of the form $\|Q\hat{f}\|^2$ subjected to the constraint $\| g - H\hat{f} \|^2 = \| n \|^2$. This process introduces large flexibility in the restoration procedure because it makes several solutions for different options of Q.[8] The additive of an equality constraint in the minimization problem can be treated by applying the procedure of Lagrange multipliers. The method is to display the constraint in the form $\alpha\left(\| g - H\hat{f}\|^2 - \| n \|^2\right)$ and then supplement it to the function $\|Q\hat{f}\|^2$, which find $\hat{f}$ that minimizes the criterion function.

$$j(\hat{f})=\|Q\hat{f}\|^2 \pm \|g-H\hat{f}\|^2 = \| n \|^2 \quad (22)$$

Where α is a constant named the Lagrange multiplier and Q the linear operator. Once the constraint has been appended, minimization is carried out in the usual way. Differentiating with respect to $\hat{f}$ and put the result amount to the zero vector products:

$$\frac{\partial j\left(\hat{f}\right)}{\partial\left(\hat{f}\right)} = \rightarrow 2Q^t Q\hat{f} - 2\pm H^t\left(g - H\hat{f}\right) \quad (23)$$

The solution is gained by solving Eq. (23) for $\hat{f}$ which is:

$$\hat{f}=(HH^t + {}^3 QQ^t)^{-1} H^t \quad (24)$$

Where $\gamma = \frac{1}{\alpha}$. This quantity must be adjusted so that the constraint is satisfied.

Such least-mean-square (Wiener) filter and constrained least-squares restoration suggested by Phillips.[8]

BASIC ITERATIVE ALGORITHM

Basic iterative algorithm form as: $\hat{f}=0$

$$\hat{f}_{k+1} = \hat{f}_k + {}^2\left(g-H\hat{f}_k\right) \quad (25)$$

Where k is number of iteration, $\hat{f}_{k+1}$ is restored image after k+1 iterations, $\hat{f}_k$ is restored image after k iterations, and β is control the convergence of the iterations.The easiest of the iterative restoration techniques has a long history. It belongs back at least to the VanCittert's work in the 1930's and may in fact have even older antecedents.[31] VanCittert's case was specially invariant and used β=1,[32] Jansson made a modification on VanCittert's work by replacing the gain β by relaxiation parameter that depends on signal,[33] even kawata used iterative restoration method with fixed and vary parameter β.[34,35]

LITERATURE REVIEW

The field of image restoration has seen a tremendous growth in interest over the past two decades. There are many excellent overview articles, journal papers, and textbooks on the subject of image restoration and identification:

1. Digital computer techniques in image restoration and enhancement had their first fruitful application at the JPL of the California Institute of Technology in 1960. As part of the program to land a man on moon, it was decided to land unmanned spacecraft initially, that would T.V back pictures of the surfs of the moon also test the soil to later other man landing, and unfortunately, the limitation on weight and power supply made it impossible to launch a "perfect" TV camera system on the unmanned craft. Consequently, JPL measures the degradation properties of the cameras before they were launch and then used computer processing to remove as well as possible, the degradation from the received moon image.[12]

2. In 1977, Hsieh and Harry[36] were studied iterative methods for both unconstrained and constrained solutions to the normal equation and presents a theoretical analysis and computational technique for constrained least squares image restoration using spline basis functions.
3. In 1988, Lanfendijk *et al.*[37] were proposed a regularized iterative image restoration algorithm, in which ringing reduction methods are included by making use of the theory of the projections onto convex sets and the concept of norms in a weighted Hilbert space.
4. In 1991, Katsaggelos *et al.*[38] were proposed adaptive and ono-adaptive algorithm based on Wiener algorithm.
5. In 1992, Charalambous *et al.*[39] were present two methods for the recovering of Nuclear Medicine images that have been degraded while being processed. The restoration problem is formulated as a constrained optimization problem. The first algorithm reduces the problem to the computation of few discrete Fourier transforms and has the ability to control the degree of sharpness and smoothness of the restored image where the input parameter can be interactively chosen by the observer. The second algorithm with weight matrices included enables the handling of edges and flat regions in the 11 image in a pleasing manner for the human visual system. In this case, the iterative conjugate gradient method is used in conjunction with the discrete Fourier transform to minimize the Lagrangian function.
6. In 1994, Jun and Park[40] were develop a new steepest descent least mean square adaptive filter algorithm.
7. In 1995, Al-Ani[17] was adapted Wiener filter and the maximum entropy method to restore optical astronomical images.
8. In 1997, Khnger[41] was adopting Wiener and homomorphic as non-iterative restoration method and an iterative restoration method based on the least-square criterion.
9. In 2000, A1-Ani and Al-Ani[42] were study image reconstruction for non-isoplanatic degradations.
10. In 2000, Al-Ani *et al.*[43]were use linear restoration filter for non-linear degradation.
11. In 2000, Ng *et al.*[44] were proposed a new approach of blind deconvolution, such as constrained total least squares image deconvolution algorithm with Neumann boundary conditions.
12. In 2000, A1-Ani[45] studied the image restoration for non-isoplanatic degradations.
13. In 2001, Ali *et al.*[46] was used an adaptive technique for image restoration, Iraqi J. of science, Vol. 42E No.2 pp.24-35.
14. In 2001, Al-Ani,[47] was used compression image restoration using modified iterated winner and homomorphic filters, Iraqi J. of science vol. 42 E no.2 pp.1-23.
15. In 2002, Ali *et al.*[48] were used maximum a posteriori technique for smoothing simulated SAR Images.
16. In 2003, Al-Ani[49] was design new filter for recovering degraded image in linear technique.
17. In 2003, Abood *et al.*[50] studied digital image blurring using hermit polynomial approximation.
18. In 2006, Al-Ani[51] was adapted in many image restorations an iterative Wiener filter. To estimate the power spectral density of the real image from degraded picture using an iterative model. The adapted filter was designed for restoring astronomical images that are blurred with space-invariant PSF and corrupted with additive noise. The result using an adaptive filter was compared, quantitatively, using mean square error (MSE). His result shows that this method has better performance for restoring the degraded images, especially for high signal to noise ratio.
19. In 2006, Charest *et al.*[52] were proposed methods for image denoising such as Osher *et al.*'s method, iterative regularization method, Iterative "Twicing" Regularization Method and Iterative Unsharp Regularization Method, using the Bilateral Filter and Total Variation Filter.
20. In 2006, Ani[53] was adapted image restoration technique using projection onto convex sets method.
21. In 2007, Al-Ani[54] studied the reconstruction of satellite images using modified statistical iterative technique.
22. In 2008, Ma[55] was formulated a new approach to medical image reconstruction from projections in emission tomography, similar to the Richardson–Lucy algorithm.
23. In 2008, Kadhom[18] was adopted different

types of restoration filters 12 such as inverse filter, Wiener filter, constrained least-squares filter, and iterative

24. In 2011, Piccolomini[56] were proposed an iterative algorithm based on constrained least squares regularization algorithm to restore the image.
25. In 2013, Amudha *et al.*[57] were proposed three restoration algorithms, namely, Local Polynomial Approximation Intersection of Confidence Interval rule, Sparse Prior Deconvolution Algorithm, and Richardson–Lucy Deconvolution Algorithm.
26. In 2013, Sureka *et al.*[58] were proposed iterative image restoration such as Wiener filter to restore the degraded face images, which improved the recognition performance and the quality of the images.
27. In 2014, Pazos and Bhaya[59] were adapted iterative gradient descent algorithms such as Barzilai–-Borwein Algorithm and the Conjugate Gradient Algorithm to restore the images.
28. In 2015, Aswathi and Mathew[60] were studied and compared various image restoration
29. In 2017, Hasan[61] were improved the quality of the degraded images by using an iterative linear restoration Tikhonov-Miller regularized restoration filter using a prior information about the degradation phenomena and Compared the obtained results from Tikhonov-Miller filter and another non iterative filter such as Wiener filter by Root Mean Square Error (RMSE) quantitative test measure.
30. In 2017, Al-Ani and Hadi[62] studied restoration of digital image using an iterative filter algorithm.
31. In 2018, Altaei *et al.*[63] recovered source image using iterative technique, MSE measurement shows that increasing iteration number gives better performance for filter, and recovering images with less degradation parameters had better performance.

CONCLUSION

Image restoration better performance when filter work on many iteration so that the image recovered from first iteration work as input for second iteration so that error decrease while number of iteration increase

This paper gives a review of different image restoration algorithms. Image restoration is a broad research area, and various researchers work to improve the efficiency of the several algorithms by developing more efficient algorithms. Image restoration is done mostly using constrained method and recently recovering real image from degraded version done by using iterative constrained technique.

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