ISSN:2320-0790

An International Journal of Advanced Computer Technology

A Review on Image Restoration in Medical Images

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Abstract: Image restoration is the removal or minimization of degradation in an image. Restoration of medical images is the demand of the hour as such images suffer from distortions like noise and blur. Medical images play a vital role in dealing with the detection of various diseases in patients and they face the problem of noise and blur. The most challenging problem is removing noise from an image while preserving its details. Restoration involves modelling of these degradations and applying inverse process to recover the original image. This paper compares various image restoration techniques.

Keywords: Medical Imaging, Image Restoration, Image deblurring, SparseRepresentation.

I. Introduction

Images are produced to record or display useful information, but the imperfect process of image formation causes image degradation. To produce a visually high quality image, image restoration or denoising is required which involves the manipulation of the image data resulting into a noise free image. Image degradation introduced by image acquisition devices because of defects in optical lenses, non-linearity of sensors, relative object camera motion, blur due to camera misfocus, atmospheric turbulence etc.

A. Degradation Model

In degradation model, the original image is blurred using degradation function and additive noise. The degraded image is described as follows:

$$g(x,y)=h(x,y)*f(x,y)+n(x,y)$$

Where g(x,y) is the degraded and noisy image, h(x,y) is the degradation function, n(x,y) is the noise and f(x,y) is the original image.(Figure 1)

The objective of restoration process is to estimate $\hat{f}(x,y)$ from degraded version g(x,y), when some knowledge of degradation function H and some noise is there.

B. Point Spread Function

The main objective of Image Restoration is to recover the original image from a degraded image which is blurred by a degradation function, commonly by a Point Spread Function (PSF). It is the degree to which an optical system blurs a point of light. The PSF is the inverse Fourier transform of Optical Transfer Function (OTF).In the frequency domain, the OTF describes the response of a linear, position-invariant system to an impulse.OTF is the Fourier transfer of the point (PSF).Image Restoration Techniques are divided into two categories on the basis of knowledge about Point Spread Function (PSF):

1) Blind Image Restoration: This Technique allows the reconstruction of original images from degraded images even when we have very little or no knowledge about PSF. Blind Image Deconvolution (BID) is an algorithm of this type. This method is difficult to implement and complicated.

2) Non-Blind Restoration: This Technique helps in the reconstruction of original images from degraded images when we have knowledge about PSF.

II. Medical Image Restoration

Image restoration techniques are used in various areas such as Medical imaging, Astronomy, Remote sensing, Forensic science, Industrial application, etc.

In this paper focused on medical image restoration because of their importance in these days and their restoration is very complicated.

A. Medical Images

Medical Images are used to detect a number of diseases which cannot be detected otherwise. But these medical images may be contaminated with noise or blur which makes the detection of the disease difficult for doctors.

There are a number of medical images such as X-ray Images, Ultrasound Images, MRI, endoscopic images, CT scan Images, Mammographic images which are useful in the detection of diseases.

III. IMAGE RESTORATION TECHNIQUES

In the past decades, different methods and filters have been used for image restoration. These methods fail to restore the image in case of different noises. Sparse representations approximate an input vector by using a sparse linear combination of atoms from an over complete dictionary. Performance of sparse representations is verified in terms of Mean Square Error (MSE) measure as well as peak signal-to-noise ratio (PSNR). Sparse based models are used in various image processing fields such as image de-noising, image de-blurring, etc.

Jan Biemond et al., proposed iterative restoration algorithms in [5] discusses the elimination of linear blur from images that contaminated by point wise nonlinearities such as additive noise and film saturation. Regularization is used for preventing the excessive noise magnification that is associated with ill-conditioned inverse problems such as deblurring problem. There are various basic iterative solutions such as inverse filter solution, least squares solutions, wiener solution, constrained least squares solution. Inverse filter is a linear filter whose point spread function is the inverse of blurring function. It requires only the blur point spread function, but it is sensitive to noise. Least Square filters are used to overcome the noise sensitivity and Weiner filter is a linear partial inverse filter which minimizes the mean-squared error with the help of chosen point spread function. Power spectrum is a measure for the average signal power per spatial frequency carried by the image that is estimated for the ideal image. Constrained least squares filter for overcoming some of the difficulties of inverse filter and of wiener filter and it also estimates power spectrum.

Michael Elad and Michal Aharon proposed KSVD method in [3] address the image denoising problem zero-mean white and homogenous Gaussian additive noise is to be removed from given image.

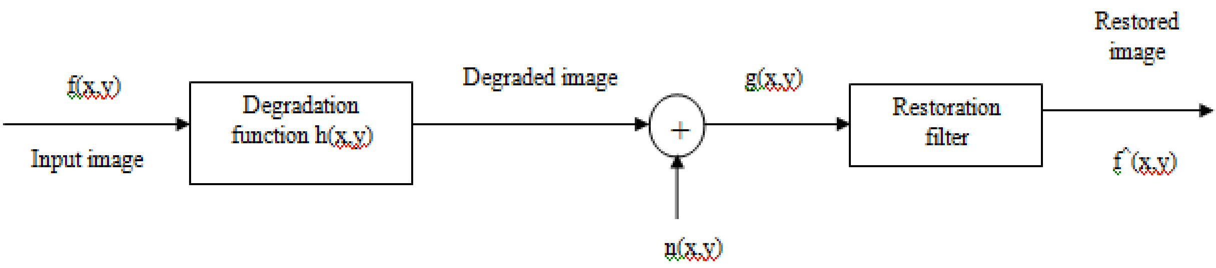

Figure 1: Image degradation Model

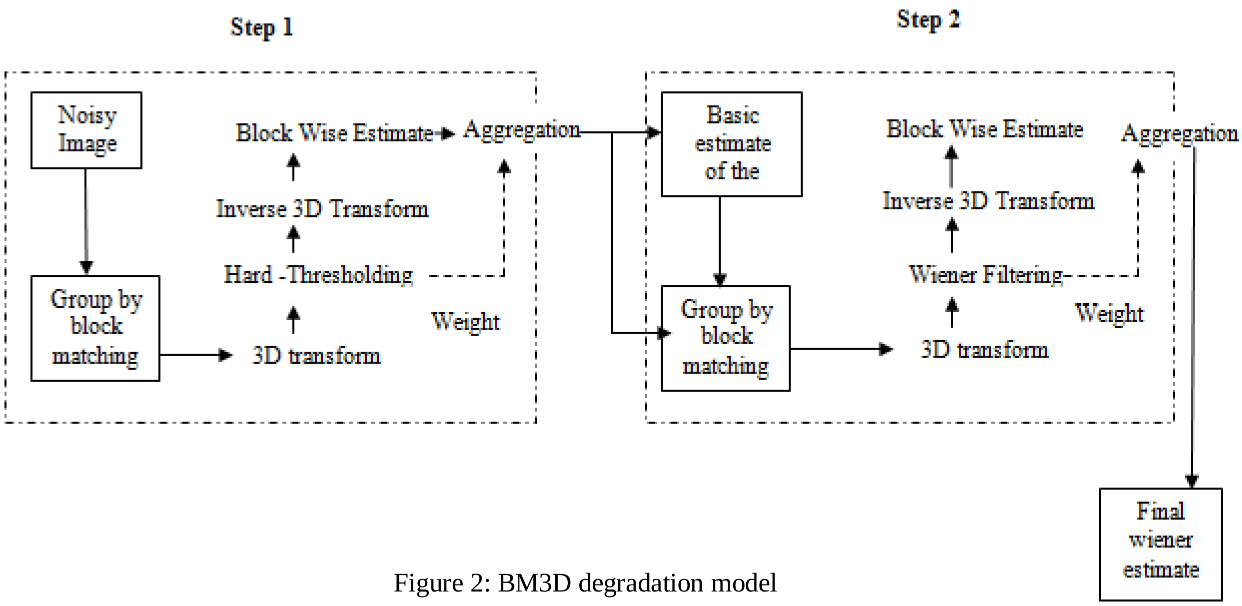

Figure 2: BM3D degradation model

Using the K-SVD algorithm, obtain a dictionary that describes the image content effectively. Dictionary trained using patches taken from a high-quality set of images or by corrupted images. Every signal is represented as linear combination of few columns (atoms) in the dictionary. Observed signal is large image patches. Sparsity of unitary wavelet coefficient was considered leading to shrinkage algorithm. Matching pursuit and basic pursuit denoising give rise to ability to address image denoising problem as a direct sparse decomposition technique over redundant dictionaries. In sparseland model Bayesian reconstruction framework is employed for local treatment on local patches to global patches. This K-SVD cannot be directly deployed on larger blocks even if provides denoising results. KSVD is simplest and fast method and it has high performance in denoising.

Leonid I Rudin et al., proposed non linear total variation based noise removal algorithms in [1] address the unavoidable noise removal in images using total variation norm. Most of image denoising methods are based on least square criteria. Proper norm for images is total variation norm. Closed form linear solutions are easily computed, nonlinear is computationally complex. Constrained minimization algorithm as a time dependent nonlinear PDE, where constrains are determined by the noise statistics. It uses TV/L_1 philosophy used to design hybrid algorithms combining denoising with another noise sensitive image denoising methods. This method denoising images by minimizing total variation norm of estimated solution. It also uses an image denoising technique called shock filter. This method preserves edges in the image and over smooth the textured regions, but it cause loss of some important details.

K. Dabov et al., proposed BM3D in [4] discusses a novel image denoising strategy on an enhanced sparse representation in transform domain. This method is based on the idea of nonlocal similarity at patch level and it works in two stages. In this there is a reference patch in given noisy image and collects similar patches that are arranged in a 3D stack. (of say some *K* patches in all). The stack is projected onto 3D transform bases. By hard thresholding the 3D transform coefficients are manipulated.

All the patches in the entire stack are reconstructed using an inverse 3D transform. This is repeated for every patch in the image. The multiple answers appearing at any pixel are averaged.

$$C_{Secondstage} = \frac{C^2_{Second-one}}{C^2_{Second-one} + \sigma^2} \quad C_{noisy}$$

Where c_i is the coefficient in 3D transformed domain. This is again repeated in sliding-window fashion with averaging.

The proposed approach can be adopted to various noise models such as additive colored noise, non-Gaussian noise etc by modifying the calculation of coefficients variances in the basic and wiener parts of the algorithm. This method can be modified for denoising 1-D signals and video for image restoration as well as for other problems that benefit from highly sparse signal representations.

Priyam Chatterjee and Peyman Milanfar proposed K-LLD method in [6] discusses a patch based locally adaptive denoising method based on clustering the given noisy image into region of similar geometric structure is proposed with the use of K-LLD. To perform clustering, employ the features of local weight function derived from steering regression. A dictionary employed to estimate the underlying pixel values using a kernel regression. With the use of stein unbiased risk estimator local patch size for each size can be chosen. Kernel regression framework uses the methods such as bilateral filter, nonlocal means and optimal spatial adaptation. Denoising can be learned with a suitable basis function that describes geometric structure of image patches. Image denoising can be first performed by explicitly segmenting the image based on local image structure and through efficient data representation. Clustering based denoising (K-LLD) makes use of locally learned dictionary that involves three steps: clustering, dictionary selection and coefficient calculation. In clustering, image is clustered using the features that capture the local structure of the image data. In second step, form an optimized dictionary that adapts to the geometric structure of the image patches in each cluster. Finally in last step, coefficients for the linear combination of dictionary atoms are estimated with respect to the steering kernel weights.David S.C Biggs [2] proposed a new method for accelerating the convergence of iterative restoration algorithms termed automatic acceleration. It means faster processing and allows iterative techniques to be used in applications where they would, otherwise seems too slow. Four different iterative methods are used for the acceleration algorithms are:

- **Richardson Lucy (R-L):** It is an iterative technique used for recovering images from poisson noise in astronomical imagery. It is an iterative algorithm for recovering images that are blured by known PSF.
- **Maximum entropy (ME) deconvolution:** is a means for deconvolving "truth" from an image and point-spread function. In a perfectly focused, noiseless image there is still a warping caused by a point-spread function. The PSF is a result of atmospheric turbulance, the instrument optics, and anything else that lies between the scene being captured and the CCD array.
- **Gerchberg-Saxton (G-S) magnitude:** The Gerchberg Saxton (GS) algorithm is one popular method for attempting phase retrieval or fourier magnitude. This algorithm can be painfully slow to

converge and is a good candidate for applying acceleration.

- **Phase retrieval algorithms:** The new method is stable and an estimated acceleration factor has been derived and confirmed by experiment. The acceleration technique has been successfully applied to Richardson-Lucy, maximum entropy and Gerchberg- Saxton restoration algorithms and can be integrated with other iterative techniques. There is considerable scope for achieving higher levels of acceleration when more information is used in the acceleration process.

Liyan Ma et al., proposed a dictionary learned approach for poisson image deblurring in [8] that discusses the deblurring of biomedical images that are caused by poisson noise. Poisson noise is arise due to quatom nature of light. Recently sparse approximation of images has shown to be efficient approaches for image recovery. In proposed model it containing three terms: a patch-based sparse representation prior over a learned dictionary, the pixel based total variation regularization term and data fidelity term capturing statistics of Poisson noise. Here patch based representation prior over a dictionary is made by using KSVD method. Using total variation regularization introduces a patch based smoothening contributes to recover textures and pixel based favoring smoothness while keeping sharp edges. Data fidelity measures distance between recovered image and observed image. This method restores noisy images into images having better signal to noise ratio.

IV. CONCLUSION

This paper compares different image restoration techniques. Sparse representations have been found to provide the better results of image restoration than other representations. Based on sparse representation, local and non-local methods can be used to restore the degraded version of images effectively. Image restoration in medical images is an active research area and various researchers work to improve the efficiency of the different algorithms by developing more efficient algorithms.

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