iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 3 **Issue:** Issue I **Month of publication:** May 2015

DOI:

www.ijraset.com
IC Value: 13.98
Volume 3, Special Issue-1, May 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Degradation Removal using Group Sparsity

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Abstract - Digital image processing has involved various processes as segmentation, classification, recognition and restoration. The image restoration has improved much by involving non-local models. The higher results are shown by Block Matching 3D Filtering and Simultaneous Sparse Coding. It involves dictionary learning to restore the degraded portion of an image. The dictionary composes of 3x3 size patches. The dictionary is made by Principle Component Analysis or Simultaneous Sparse Coding in the existing system. The Group Sparsity involves restoring group of patches to the image. The dictionary is created by Singular Value Decomposition method and selection of patches by using Single Value Thresholding method. The L_0 optimization occurred in group sparsity is reduced by Split Bregman iteration method. The time complexity of restoration is reduced by the proposed system. The higher PSNR value is achieved by group sparsity method.

Index terms--- Block Matching 3D Filtering, Discrete Cosine Transform, Principle Component Analysis, Split Bregman iteration

I. INTRODUCTION

Digital images are electronic snapshots taken of a scene composed of picture elements in a grid formation known as pixels. Each pixel holds a quantized value representing the tone at a specific point. The formation of digital images can be described by the pinhole camera model as a point and only the light from the scene passes through the camera aperture can be captured on the image plane. The camera aperture has a finite size and is often appended with a lens to focus light from the object in the scene. The deviation of the digital image from the actual depiction of the scene can be described as distortion and it may be resulted from both hardware and software processing limitations. The observed or distorted image $i(x, y)$ can be modeled as a convolution of the object function $o(x, y)$ in the actual object in the scene and the image degradation function $h(x, y)$.Equation.1 is known as the point spread function.

$$i(x, y) = o(x, y) ** h(x, y) + n(x, y) \qquad (1)$$

where $n(x, y)$ is an additive noise function describing the random variation of the pixel intensity. The restoration involves enhancement of images and removal of degradation. The difference is that restoration produces objective measure but not subjective The degradation may be resulted due to defects occurred in image acquisition.Fig.1 shows image degradation and restoration process.

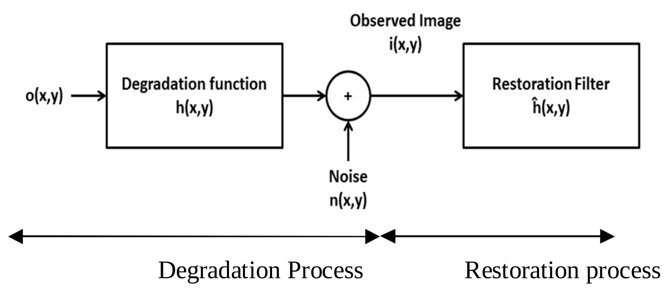


Fig.1 Image degradation and restoration block diagram

The restoration process can be done by using various filters. The filters employed can be linear or anisotropic. The linear filters work by convolving original image with mask. The anisotropic filters work by diffusion done perpendicular to the image. The filters are applied to various noises. The restoration process is quite simple but the actual implementation of filters is difficult. The filters must require degradation function and type of noise to be known in prior.

The restoration can also be done by using non-local means algorithm [1]. The Non-Local means is the averaging of non-local pixels in the image. The NL means algorithm provides better performance than filters. Various approaches of image restoration has been studied in ([1]-[6], [15], [16], [18], [20]).

II. RELATED WORK

The importance of singular value decomposition [12] and its advantages such as stability, low rank approximation of matrices is introduced for image restoration. Decomposition can be achieved by unitary matrices. It can be applied for Spatially Adaptive Iterative Single value Thresholding (SAIST) algorithm [22] in case of minimizing matrix during iterative regularization. A novel method called Deterministic Annealing method [13] for clustering has achieved good results than other thresholding methods in case of inpainting. The method introduces equi-probable contours as cluster regions and it is used for clustering and classification. Block Matching [3] achieved the sparsity by grouping similar 2D image fragments into 3D data arrays called as groups. Collaborative filtering is a special procedure developed to deal with these 3D groups. The collaborative filtering reveals even the nest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block. The new approach of soft decision interpolation [23] for estimating missing pixels in groups preserves spatial coherence of interpolated images better than previous methods and it produces the best results in both Peak Signal to Noise Ratio (PSNR) measure and subjective visual quality. The self similarity of images is focused in [4] for natural images to average out noise among similar patches and sparse coding encodes natural image statistics by decomposing each image patch into a linear combination of a few elements from the basis set called dictionary. It has been applied only to uniform noise models and it does not applied for image inpainting and texture synthesis. A low rank approach [9] is applied to the problem of matrix approximation. It involves soft thresholding operation on matrices. The convergence problem is occurred due to non-decreasing threshold value. The iterative regularization procedure for inverse problems is introduced in [14]. It is based on the use of Bregman distances. The method motivates the problem of restoring noisy and blurry images through variational methods by using total variation regularization. The iteration starts with initial vector and it proceeds until the threshold is reached for spatial adaptation. A new formulation for denoising images by using iterative refining cost function is given in [17]. Iterative twicing regularization and unsharp regularization are used to denoise and deblur images. The second method derived by author provides better results among all methods. The proposed method can also be extended to update the noise variance and signal variance. The new approach to solve L_0 optimization problem is two step iterative shrinkage thresholding methods [8]. The aim is to solve linear inverse problems. The method will consider the result of last two previous iterates than only one iterate. A fast iterative shrinkage thresholding for linear problems and a monotone version of it for non linear inverse problems are derived. A fast gradient algorithm [7] was used to solve deblurring and denoising problems. The algorithm used is gradient projection dual approach method. The iteration used is Fast Iterative Shrinkage Thresholding. It combines with both gradient projection and fast gradient projection. The fast gradient projection scores over gradient projection in solving sub-problems of denoising. A new method for solving L_0 minimization problem with Bregman iteration for compressive sensing is introduced in [11]. The basic idea of Split Bregman iteration is to solve the problem of L_1 minimization. The methodology is to convert unconstrained problems into constrained one and solve it by Bregman iteration. The result shows good convergence property but it could be applied only for basis pursuit problem.

III. BLOCK MATCHING 3D FILTERING

The block transformation [3] is a novel technique used to denoise an image. It involves 3d transformation of image blocks. Initially a reference block is fixed and the similar blocks are obtained by using similarity measure Euclidean distance. The similar blocks are grouped to form 3d blocks. The basic estimate is obtained by using thresholding or by using wiener filtering. Each fragment will produce its own estimate and by weighted averaging, overall estimate is obtained for the block. The final estimate of an image is obtained by aggregating the estimates of all pixels. The block matching method can be adapted to various noise models such as additive colored noise and non- gaussian noise by modifying the calculation of coefficients variances in the basic and Wiener parts of the algorithm. The developed method can be modified for denoising 1D-signals and video [6] for image restoration and for other problems to benefit from highly sparse signal representations.

IV. SIMULTANEOUS SPARSE CODING

The non local image model exposes self similarity of an image. The combined approach of sparsity and self-similarity will lead to Simultaneous Sparse Coding (SSC). The SSC technique used basis set called dictionary. The dictionary collects patches from various images. Each patch is of size 9 x 9. The dictionary can be created by using Discrete Cosine transformation or Principle Component Analysis. The SAIST algorithm [21] combines sparsity versus self-similarity by using SSC.

Volume 3, Special Issue-1, May 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

V. SAIST ALGORITHMS

Simultaneous sparse coding (SSC) or group sparsity has shown great potential in various low-level vision tasks, leading to several state-of-the-art image restoration techniques. A low-rank approximation (LA) approach toward SSC and provide a conceptually simple interpretation from nonlocal variance estimation perspective is introduced in nonlocal sparsity based restoration. It resulted in two spatially adaptive iterative singular-value thresholding (SAIST) algorithms for noisy and incomplete observation data. For noise data, the algorithm generalizes existing BayesShrink from local to nonlocal models and for incomplete data and the algorithm extends previous deterministic annealing based techniques ([19], [13]) by incorporating the idea of dictionary learning.

A. Image denoising

It is a technique to remove noise from degraded images. The denoising involves various methods other than filters ([2], [5], [15]) for reconstruction of image. It is done by using dictionary learned from Discrete Cosine Transform (DCT) or Principle Component Analysis (PCA).The degraded image will be divided into patches. Each patch will be iterated over test image. The similarity measure is calculated for each iteration. Based on the measured Structural Similarity Measure (SSIM) the patches are clustered and undergo thresholding to remove noise. The final image is upgraded by weighted averaging of all similar patches.

B. Image completion

It is done by technique called Inpainting. Inpainting is a kind of technique in image restoration. The user will select the region to be restored and the algorithm will automatically fills-in these regions with information surrounding the inpainting area. The fill-in is done in such a way of arriving isophote lines at the regions boundaries are completed inside. The technique used does not require the user to specify the novel information about the lines. It is automatically done in a fast way, allowing to simultaneously fill-in numerous regions containing completely different structures and surrounding backgrounds. No limitations are imposed on the topology of the region to be inpainted. The inpainting [16] is completed by using dictionary containing patches. The image to be inpainted will undergo iterative regularization with the patches. The threshold value is calculated on each iteration by using Deterministic Annealing (DA). It proceeds until the threshold value selected will complete the image. The image is upgraded finally by updating the dictionary.

VI. OPTIMIZATION PROBLEM

The image restoration involves the problem of L_0 optimization due to dictionary with more similar patches. Various methods for solving L_0 minimization problem has been studied in ([7], [8], [10]). The L_0 optimization can be taken as L_1 problem in some technical cases. The L_1 optimization problem could be solved by Split Bregman iteration [21]. The L_0 optimization has been applied for compressed sensing in [11]. The Bregman iteration could involve optimization of dictionary and solve the problem of minimization. The Split Bregman algorithm is

Step 1: Set t=0
Step 2: Repeat
Step 3: $u^{(t+1)}=\text{argmin}_u\, f(u)=\frac{\mu}{2}\, ||u-Gv^{(t)}-b^{(t)}||_2^2$
Step 4: $v^{(t+1)}=\text{argmin}_v\, g(v)=\frac{\mu}{2}\, ||u^{(t+1)}-Gv-b^{(t)}||_2^2$
Step 5: $b^{(t+1)}=b^{(t)}-(u^{(t+1)}- Gv^{(t+1)})$
Step 6: t=t+1
Step 7: until stopping criterion is reached.

VII. PROPOSED WORK

The group sparsity is combined with self adaptive dictionary reduces the complexity of missing patches in the dictionary. The L_0 minimization problem will be solved by Split Bregman iteration.

A. Image deblurring

The steps involved in image deblurring is

Step 1: Blur the image with Gaussian function.
Step 2: Decomposition of image into patches to form dictionary.

Step 3: The similar patches could form clusters.

Step 4: The singular value decomposition is used to learn dictionary.

$$svd(A)= USV^T \qquad (2)$$

where A= input image

U= rows entries of image patch

V= column entries of image patch

S= diagonal entries containing Eigen vectors.

Step 4: Split Bregman iteration of patches onto the image to restore the image.

Step 5: The dictionary and sparse coding coefficients updated at the end of final iteration.

Step 6: Image updated by using resulted dictionary.

B. Image inpainting

The image inpainting involves the same steps to complete the image. The mask involving diagonal entries are used to complete the image instead of blur operator. The idea is to cover pixels in the neighborhood value to cover the incomplete region.

Step 1: Give the input image.

Step 2: Add any mask with text or random noise over the image.

Step 3: Construct the dictionary for each group by using Single value decomposition.

Step 4: Update the overall dictionary for entire image by combining all group dictionary elements.

Step 5: Update sparse coding coefficients of image by using hard thresholding.

$$\boldsymbol{\tau} = (\lambda K) / (\mu N)$$

where = Threshold

λ , μ = Constant for calculating threshold

K= size of patch group

N= total number of iteration

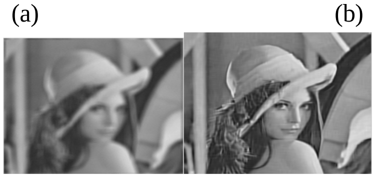
Step 6: Derive each iteration of patch and find the matched patch from the dictionary.

Step 7: Restore the image with final constructed dictionary and sparse coding co-efficients.

VIII. EXPERIMENTAL RESULTS

The experimental results of Group Sparsity method is obtained with higher PSNR value than other previous methods. The sample gray images of size 512X512 are taken as input. The iteration count of six produces higher rate of convergence. The result of deblurring shows the success in removal of blur from the images. The performance measure is given in Table 1. The deblurring results are shown in Fig.2.

(a) (b)



(c) (d)

(e) (f)

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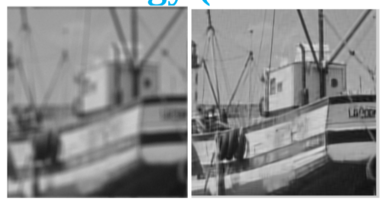


(g) (h)

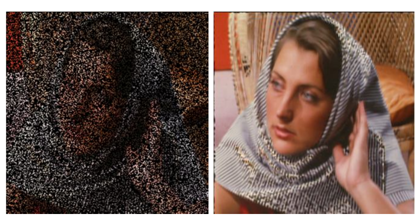
Fig. 2 Results of deblurring a) Degraded Barbara image b) Deblurred Barbara image c) Degraded Lena image d) Deblurred Lena image e) Degraded cameraman image f) Deblurred cameraman image g) Degraded boat image h) Deblurred boat image

Image	Original PSNR	Final PSNR
Barbara.tif	25.59	28.05
Lena.png	22.44	30.59
Cameraman.tif	20.75	27.11
Boat.tif	22.27	30.79

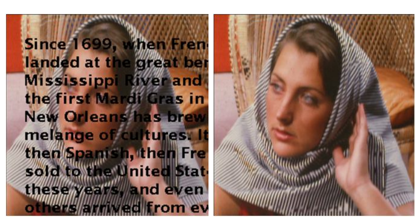
Table.1 Performance of group sparsity with Split Bregman iteration

The ten iterations of two images have taken elapsed time of 4.131 min. The choice of choosing similar patch in the dictionary involves more time to restore the image. The action of self adaptive dictionary eliminates the missing patch condition. The group sparsity involves only few iteration using Split Bregman iteration. It reduces the time complexity of SAIST algorithm.

(a) (b)



(c) (d)



(e) (f)

Volume 3, Special Issue-1, May 2015
ISSN: 2321-9653

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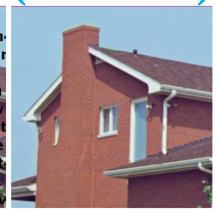

(g) (h)

Fig. 3 Results of in-painting a) Noisy House image b) Restored House image c) Noisy Barbara image d) Restored Barara image e) Barbara image with text f) Restored Barbara image g) House image with inpainted text
h) Restored House image

The inpainting application is done with two degradation such as text in-painting and pseudo random noise addition. The House image is added with 0.2 random noise and Barbara image is added with 0.3 random noise. The text is another image inpainted with original image and Group Sparsity method restore the image with little degradation. The PSNR values for the images are given in Table.2.

Image	Original PSNR	Final PSNR
Noisy House image	29.81	32.51
Noisy Barbara image	22.64	23.72
Barbara image with text	29.08	32.38
House image with text	36.60	40.50

Table.2 Inpainting results in Group Sparsity method

The Group Sparsity proves its result in in-painting by examining color images to improvise the visual quality. The SAIST algorithm shows denoising results to get converged in L_0 iterations as shown in Fig.4. The PSNR value needs more than 3 minutes to restore the image.

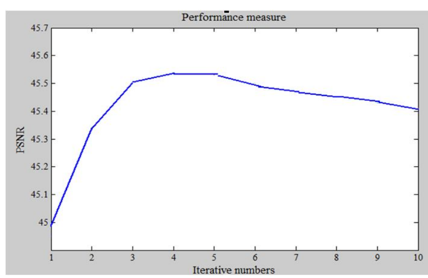

Fig.4 Convergence level of SAIST algorithm

Fig.5 shows the results of group sparsity with Split Bregman iteration. The new iteration will reduce the time complexity by solving L_0 minimization problem. The convergence is obtained within few iterations.

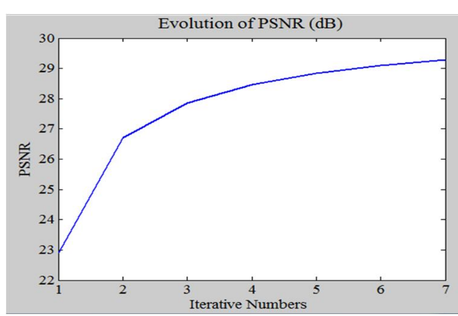

Fig.5 Convergence level of Bregman iteration method

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IX. CONCLUSION

A general framework for high-quality image restoration using group-based sparse representation modeling is achieved and it sparsely represents natural images in the domain of group. It explicitly and effectively characterizes local sparsity and nonlocal self-similarity of natural images simultaneously in a unified manner. An effectual self-adaptive group dictionary learning technique with low complexity is designed. High sparsity degree and high recovery quality is achieved by group based sparsity method. It proves its result in the area of image deblurring and inpainting. The PSNR value calculated in the group sparsity method is greater than previous algorithms used in image restoration. The Split Bregman method could solve L_0 minimization problem efficiently. The optimization solution will eliminate the issues in time complexity. Thus group sparsity with the self adaptive dictionary will proves better results in image restoration.

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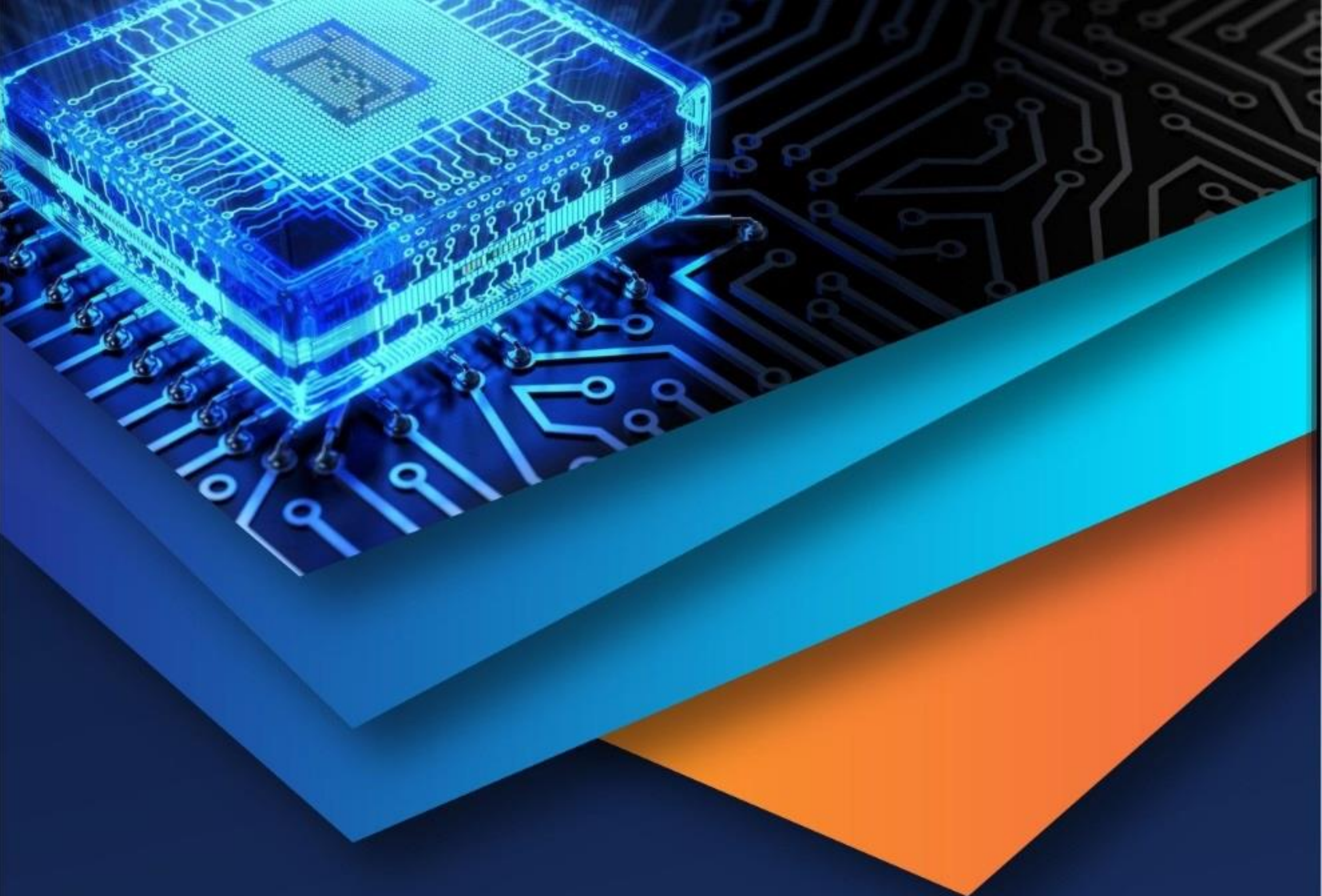

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