IMAGE RECONSTRUCTION FROM INCOMPLETE AND NOISY DATA USING PROJECTION BASED DEBLURRING

Mr. M.Yasin[#1], Mr. AR.Arunachalam*[2]

Post Graduate Student, Department of Computer Science& Engineering,
Bharath University, Chennai-73
Email:yasi.jack03@gmail.com
Assistant Professor, Department of Computer Science& Engineering
Bharath University, Chennai-73
Email:ararunachalam78@gmail.com

Abstract - Image processing is important on various fields to achieve various functions. In this paper two classes of regularization strategies to achieve image recovery and reduce noise suppression from Original image in projection-based image deblurring. Landweber iteration leads to a fixed level of regularization, which allows us to achieve fine-granularity control of projection-based iterative deblurring by varying the value. Regularization filters can be gained by probing into their asymptotic behavior—the fixed point of nonexpansive mappings. Different image structures (smooth regions, regular edges and textures) are observed correspond to different fixed points of nonexpansive mappings when the temperature (regularization) parameter varies. Such an analogy motivates us to propose a deterministic annealing based approach toward spatial adaptation in projection-based image deblurring.

Keywords – Projection-based image deblurring, Fine granularity regularization, Nonexpansive mapping.

I. INTRODUCTION

Images are produced to record or display useful information, but the process of image formation and recording is imperfect. The recorded image invariably represents a degraded version of the original scene. The recovery of an image from its noisy and blurred version has been well studied in a period of ten years. A prior knowledge “based on the true solution or noise into the solution algorithm’. There are two frameworks for implementing regularization namely projection-based deblurring and variational-based deblurring. In projection based deblurring the knowledge based on true solution is used i.e. prior knowledge.

The first encounters with digital image restoration in the engineering community were in the area of astronomical imaging. The astronomical imaging degradation problem is often characteristic by poison noise. Another type of noise found in other digital imaging applications is Gaussian noise, which often arises from the electronic components in the imaging system and broadcast transmission effects. Astronomical imaging is still one of the primary applications of digital image restoration today. Not only is it still necessary to restore various pictures obtained from spacecraft such as the initial Hubble telescope (HST).under the framework of projection-based image deblurring we make the following new contribution to this work.

- Fine-granularity regularization. To find out the equivalence between Landweber iteration and projection into the convex set using r-times Landweber iterations to achieve fine-granularity regularization in projection-based deblurring. In variational framework the regularization parameter is equivalent to a weighted deblurring function. Eigen value analysis is used to illustrate how such weighting strategy on deblurring functional can achieve a better tradeoff between image recovery and noise suppression.
- Spatially-adaptive regularization. Decrease the regularization parameter to achieve spatial adaptation. Image processing is used to illustrate the asymptotic behavior of both local and nonlocal regularized filters. Regularization parameter in image processing plays a important role of temperature and different structures. The technique of deterministic annealing popular for nonconvex optimization problems is effective on achieving spatial adaption.

ISNR (improved signal to noise ratio) is compared to find out the regularization strategies. The main purpose of this project is study two classes of regularization strategies, namely fine-granularity regularization and spatially-adaptive regularization. Fine-granularity is defined as it is the extent to which a system is broken down in to small parts or a larger entity is subdivided and spatial-adaptive regularization is defined as structures in photographic images such as edges and textures visible or clear nonlocal dependency or regularity. Block diagram is explained in Fig.1

The value of unified projection-based framework is that it allows us to understand various image deblurring algorithms in a principled manner. From this perception, many deblurring algorithms based on different heuristics and can be viewed as a combination of sequential and parallel projections strategies, any iterative image deblurring algorithm has been called relaxation control, which is abstractly equivalent to regularization.

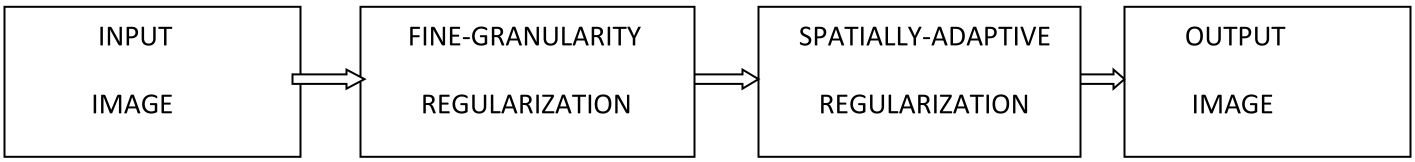

Fig. 1 System Design

II. ITERATIVE REGULARIZATION

Projection based iterative deblurring is to be focus for the knowledge about true solution. Noisy burred image along with the degradation model specify the other set called observation constraint set. In variational iterative deblurring, regularization functional conveying the prior information.

$$\boxed{\mathbf{g=Hf+w}}$$

Where **f, g** are lexicographical stacked representation of blurred and un blurred images, **H** is the blurring operator and **w** denotes the white Gaussian noise with zero mean and variance $\boldsymbol{\sigma}^2_{w}$.

$$\boxed{J_\lambda(\boldsymbol{f}) = \| \boldsymbol{g} - \boldsymbol{Hf} \|^2 + \lambda \boldsymbol{J}(\boldsymbol{f})}$$

Langrangian multiplier is often called as regularization parameter as it controls the tradeoff between image recovery and noise suppression. The major difference between various deblurring techniques lies in the selection of regularization and wavelet-based. We are comparing various regularized filters by viewing them as nonlinear projection operators and inspecting their asymptotic behavior. Filtering algorithm is based on heuristics instead of principles in image processing. After applying iterative regularization the Improved (SNR) ISNR value is 8.5853 for house image.

Fig. 2 Denoised Image Using Iterative Regularization

The output image obtained using iterative regularization is shown in fig. 2.

III. FINE-GRANULARITY REGULARIZATION

In variational image deblurring, the degree of regularization is controlled by the regularization parameter λ. But projection based deblurring is not feasible to derive analytical function r times Landweber iteration is equivalent to scaling the regularization parameter λ by a factor of $1/r$. we propose to minimize the following weighted deblurring functional

$$\boldsymbol{fk+1=fk+\beta(g-Hfk)}$$

β blurring operator generalizes the definition of deblurring error. The motivation behind the proposed deblurring functional has two folds. First introduction of β_i operator that generalizes the conventional definition of deblurring error. Second, weighted deblurring functional improves the numerical stability of Landweber iteration. It is proved by applying Eigen value analysis to the linear system. Eigen vectors associated with blurring operator **H** and the corresponding Eigen values λ_{mn} .the term fine-granularity is used to emphasize the increased flexibility in manipulating the procedure of relaxation control. In addition to r-times Landweber iteration. It is feasible to combine it with a spatially adaptive control strategy. Original image of cameraman is shown in figure 3 and the output image obtained using fine-granularity is shown in figure 4.

Fig. 3 Original Image

texture of photographic films. There are some local approaches that highlight spatial adaptations from a local smoothness perception. The limitations of such approaches is important in photographic images such as edges and textures obvious nonlocal dependency or reliability. annealing is popular for nonconvex optimization problems nonlocal regularization are referred as functional classes capable for exploit nonlocal dependencies along edges and there are two techniques used in spatially adaptive regularization and they are Nonlocal Total Variation (NLTV) and Block-Matching 3-D (BM3D). Both Nonlocal total variation and Block-matching 3D are used because of their striking performance in image recovery.

IV. SPATIALLY ADAPTIVE REGULARIZATION

Gradually decrease the regularization parameter to achieve spatial adaptation. Analogy between statistical physics and image processing is used to illustrate the asymptotic behavior of both local and nonlocal regularized filters. It is shown that regularization parameter in image plays a similar role of temperature parameter in statistical physics and different structures in image processing.

Fig. 4 Fine-Granularity Image

The technique of deterministic annealing is popular for nonconvex optimization problems nonlocal regularization are referred as functional classes capable for exploit nonlocal dependencies along edges and there are two techniques used in spatially adaptive regularization and they are Nonlocal Total Variation (NLTV) and Block-Matching 3-D (BM3D). Both Nonlocal total variation and Block-matching 3D are used because of their striking performance in image recovery

Algorithm 1.Projection-based image deblurring with fine-granularity and spatially-adaptive regularization

Input: noisy blurred image **g**, blurring kernel **H**, noise level $\boldsymbol{\sigma_w}$, regularization parameter r, T_0 or λ_0 and step size Δ;

Output: Estimated image $\hat{\hat{\hat{f}}}$

- Initialization: set initial condition $\boldsymbol{f}(0) = \beta \boldsymbol{H} * \hat{g}$;
- Main loop: for k=1, . . . ,$k_{max,}$ set

$T_k=T_0-(k-1)\,\Delta$ or $\lambda_k=\lambda_0(1+\Delta)^{-(k-1)}$

__Projection onto the observation constraint set:

$f^{k+1/2}=P_{lw}^{(r)} f^k$;

__projection onto the prior constraint set:

$f^{k+1}=P_{rf}\, f^{k=1/2}$ where P_{rf} can take any form of regularized filtering

__calculate $e^{(k)}=\| f^{(k)}-f^{(k-1)} \|$,if

$e^{(k)} > \max\{ e^{(k-1)},\ldots, e^{(k-d)}\}$ return $\boldsymbol{f}(k)$;

V.EXPERIMENTAL RESULTS

We are going to find out the ISNR value of the images and after fine-granularity and spatial-adaptive regularization methods are applied we are comparing the result with various images like present and previous image. So that we can able to prove the efficiency of this project. dB is used to measure ISNR value. The images that are having more than 9dB is said to be a clarity image. In this project we are obtaining more than 10dB. the ISNR values differs according to the images that we are going to use as input

A. comparison with model variants

In this module we are going to demonstrate in what way fine-granularity and spatial-adaptive regularization strategy works and the noise level specified by Blurring SNR (BSNR) is defined as

$$\mathrm{BSNR} = 10 \log 10 \frac{\sigma_g^2}{\sigma_w^2} (\mathrm{dB})$$

Where σ denotes the variance of the blurred image g=**H**f and noise respectively. The value of BSNR used is 40 dB corresponding to light, medium and noise. The deblurring algorithms is also compared for visual examination to check for the performance and it is compared in terms of improved SNR (ISNR).

$$\mathrm{ISNR} = 10 \log 10 \frac{\|\mathbf{g} - \mathbf{f}\|^2}{\|\hat{\mathbf{f}} - \mathbf{f}\|^2} (\mathrm{dB}).$$

The image f is standard 256 × 256 and the blurring kernel is 9 × 9 uniform.first r is used in projection-based deblurring and λ plays a important role in varational-based deblurring. We have compared the ISNR value with two different parameter r and λ respectively by varying the noise level. Second we are going to compare two classes of projection operators, local vs nonocal filtering. The comparison of asymptotic behaviour among different regularised filters is relevant to image deblurring because it allows us to inspect the solution specified by the prior knowledge.

B. Spatial Adaptation Via Deterministic Annealing

It is easy to identify non-convexity of prior constraint set because the collection of image patches of the same size in photographic images form a low dimensional manifold, one way of conceptually visualizing such image manifold is that it is decomposed of several constellations: smooth regions,regular edges and textures.

- Starting with a high parameter, it is relatively easier to find a reliable local optimum because the constellation of smooth regions is approximately convex.
- As the temperature gradually decreases,the functional costs gets strong and less convex
- As the temperature keeps decreasing and reaches the new phase.

C. Comparison With Other Competing Methods

There are three recent works introduced on image deburring and they are TV based on majorization-minimization (TVMM) , Shape-adaptive DCT and iterative shrinkage or thresholding (IST), have been chosen as benchmark schemes in our project. Figure 5 shows the comparison of images using different image deblurring algorithms and methods.

TABLE 1. SHOWS THE COMPARISON OF ISNR VALUES OF DIFFERENT IMAGES.

Image (256 × 256) PNG	**ISNR (dB)**
Cameraman	9.96
Lena	10.09
House	12.15
Barbara	9.9

Fig. 5 comparison of original cameraman images,noisy blurred image (BSNR = 40 dB, 9 × 9 uniform blur) and deblurred images by different agorithms);a) Original image; b) Noisy blurred image; c) TVMM (ISNR = 8.48 dB); d) SADCT (ISNR = 8.57 dB); e) IST (ISNR = 8.65 dB) ; f) fine-granularity and spatail-adaptive regularization (ISNR = 9.96 dB).

TABLE 2.SHOWS THE COMPARISON OF DIFFERENT IMAGE DEBLURRING ALGORITHMS

FOR NONUNIFORM BLURRING KERNEL AND NOISE LEVEL.

Image BSNR	**House 40 dB**	**Lena 40 dB**	**Cameraman 40 dB**	**Barbara 40 dB**
TVMM	6.64	4.99	8.48	1.34
SADCT	5.48	5.06	8.57	4.06
IST	6.17	5.88	8.65	2.86
Fine-granularity & Spatial-adaptive	**7.00**	**6.77**	**9.96**	**5.06**

TABLE 2 describes the various ISNR values obtained from various images. The format of the image used is PNG and the size is 256 × 256. Table 2 describes the comparison of different deblurring algorithms for 5 × 5 nonuniform blurring kernel and noise level.

VI. CONCLUSION

We have revised the problems of iterative image deblurring under a projection-based framework. Our project has twin contribution one is to generalise the existing variational formulation and the other is to understand the nonlocal regularised filtering by probing into their asymptotic behaviour based on fixed-point. In our project we are using blurring kernel,noise level and four test images.

REFERENCES

[1] M. Figueiredo and R. Nowak, "An em algorithm for wavelet-based image restoration," *IEEE Trans. Image Process.*, vol. 12, no. 8, pp.906–916, Aug. 2003.

[2] A.Chambolle, "An algorithm for total variation minimization and applications,"*J. Math. Imag. Vis.*, vol. 20, no. 1, pp. 89–97, 2004.

[3] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman,"Removing camera shake from a single photograph," *ACM Trans.Graph.*, vol. 25, no. 3, pp. 787–794, 2006.

[4] O. G. Guleryuz, "Nonlinear approximation based image recovery using adaptive sparse reconstructions and iterated denoising—Part II:Adaptive algorithms," *IEEE Trans. Image Process.*, vol. 15, no. 3, pp.555–571, Mar. 2006.

[5] E. Ok, *Real Analysis With Economic Applications*. Princeton, NJ:Princeton Univ. Press, 2007.

[6] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-d transform-domain collaborative filtering," *IEEE Trans.Image Process.*, vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[7] P. Brianzi, F. Di Benedetto, and C. Estatico, "Improvement of space invariantimage deblurring by preconditioned Landweber iterations,"*SIAM J. Sci. Comp.*, vol. 30, pp. 1430–1458, 2008

[8] P.Vandewalle, J.Kovacevic, and M.Vetterli, "Reproducible research insignal processing—What, why, and how," *IEEE Signal Process. Mag.*,vol. 26, no. 3, pp. 37–47, May 2009.

[9] X. Zhang, M. Burger, X. Bresson, and S. Osher, "Bregmanized nonlocal regularization for deconvolution and sparse reconstruction,"*UCLA CAM Rep.*, pp. 09–03, 2009.

[10] X. Bresson, A Short Note for Nonlocal TV Minimization technical report,Jun. 2009.

