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Regularized Multichannel Blind Deconvolution Using Alternating Minimization

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** Regular Paper*

Abstract**:** Regularized Blind Deconvolution is a problem applicable in degraded images in order to bring the original image out of blur. Multichannel blind Deconvolution considered as an optimization problem. Each step in the optimization is considered as variable splitting problem using an algorithm called Alternating Minimization Algorithm. Each Step in the Variable splitting undergoes Augmented Lagrangian method (ALM) / Bregman Iterative method. Regularization is used where an ill posed problem converted into a well posed problem. Two well known regularizers are Tikhonov class and Total Variation (TV) /L2 model. TV can be isotropic and anisotropic, where isotropic for L2 norm and anisotropic for L1 norm. Based on many probabilistic model and Fourier Transforms Image deblurring can be solved. Here in this paper to improve the performance, we have used an adaptive regularization filtering and isotropic TV model Lp norm. Image deblurring is applicable in the areas such as medical image sensing, astrophotography, traffic signal monitoring, remote sensors, case investigation and even images that are taken using a digital camera /mobile cameras.

1. Introduction

This paper proposes Multichannel Blind deconvolution using Alternating Minimization Algorithm. Application of deconvolution is required on degraded images and that can be medical image, astronomical image, normal colour image etc. Now it is important to know, how an image become degraded? This can be basically by two phenomenon. Deterministic and random nature. Where deterministic nature is appeared as blurred image, and random nature as noise on images. Blur kernel is called point spread function (PSF). It is convoluted to image and noise is added on to image. y be the resultant blurred image and y € R^{n^2}.

It follows the equation:

$$y = h * x + w \tag{1}$$

Where, blur represented as h € $R^{n^2 \times n^2}$, noise as w€ R^{n^2}, original image represented as x € R^{n^2}.

Blind deconvolution [1] is a problem in order to bring an image out of blur and the noise can be eliminated, where single channel deconvolution fails for noisy or the images without salient edges. For Multichannel, proper regis- tration of input blurry image should be done. Deconvolution is a problem where it can be blind and non blind depending upon the unknown variables where it is a well posed or ill posed problem. First we will see the blind deconvolution in order to obtain H value and by using that value we will reconstruct the deblurred image i.e., X value and this is called non blind deconvolution. Blind deconvolution [2-5] is a problem in order to bring an image out of blur and the noise can be eliminated here. Then the problem in which it will be a simple inverse problem; if the blur kernel is known. The blind deconvolution is to obtain the blur kernel using some iterative algorithms such as Maximum A posterior (MAP) and Alternating minimization algorithm. In order to preserve sharp edges we use Multichannel blind deconvolution instead of single channel.

The Eq. (1) modified as follows:

$$y = h * x \quad (2)$$

In order to do inverse filtering effectively convert it in to frequency domain there by convolution changed in to multiplication. Blurring can be occurred due to several reasons such as atmospheric conditions and camera shaking [23] and lens imperfection. First consider the single channel deconvolution and then later with multi-channel deconvolution, for that here we use green channel first because it gives more details of image than other two channels. To improve the performance we have used an adaptive regularization technique that gives better quality reconstructed image .The quality can be analyzed using a parameter Peak Signal to Noise Ratio (PSNR)

1.1 Proposed Work

This work proposes the image deblurring using MC blind deconvolution via Alternating Minimization Algorithm. Here noise term (w) is eliminated. Lp norm along with adaptive regularization gives better results than L2 norm with adaptive regularization. This algorithm suites very well as it can be effectively solve for two variable unknowns. As two variables are unknown it become indirect solution method and it uses the Bregman iteration along with ALM equation to solve this. The ill posed problem can be solved using adaptive regularization so that additional weight or penalty added to improve the performance and also the masking filter of 3x3 matrix and 2D Laplacian kernel gives better results. The directional prior which uses 3 directions such as x,y and z. This can be simulated using MATLAB software. The resultant PSNR value can be compared with the previous work to analyse the quality of the image after deblurring.

2. Adaptive Regularization

As it is a blind deconvolution the number of unknowns are not equal to number of variables hence called ill-posed problem [6]. In order to solve for PSF using inverse filtering it should be a well posed problem. The process of converting the ill-posed problem to well posed problem called regularization. One of the simplest approach is inverse filtering, it is least mean square estimation using maximum likelihood approach. $\|hx - y\|^2$ is the basis least square mean but for image deblurring as it is ill posed it requires an additional term called regularizer

Ø(x); where Ø(x) = ||x||(norm 1 or 2). Least square mean can rewrite as follows:

$$\min_x M(x) = \Phi(x) + \left(\lambda/2\right)\|hx - y\|^2 \quad (3)$$

where parameter λ is used to balance two terms

2.1 Isotropic TV model

In this paper isotropic TV model uses l_p norm instead of l_2. It is known as Moore Penrose Pseudo inverse and are also called Least square problem. It can be solve using Lagrange multipliers. As l_1 optimization result in smooth nature there it will not be a best solution for our problem.

Here we used blind deconvolution using Augmented Lagrangian Method (ALM). This can be solved efficiently using variable splitting method and there by applying Bregman Iterative method.

The blur regularizers and image regularizers which are not smooth and thereby introduces non linearity problems. l_1 norm is linear where as l_2 norm is non linear [10] if it alternating using both norms the non linearity problem arises, this brings direct minimization as slow process. In order to overcome these problems use the auxiliary variables and split this step into two simple minimization steps. And solve it using ALM.

The drawback that occurring due to regularizers that is convergence difficulty and more ill posed by increasing the regularizer term this can be overcome by using ALM i.e, it will converges to the required minimum even the regularizer is fixed or small. The weight of the parameter β and λ update in each iteration till the convergence meets. This improves the quality of the reconstructed image. Peak signal to noise ratio comparison can be done between regularized and adaptively regularized method. D_x , D_y and D_z are Derivatives with respect to x, y and z. R(h) is the blur regularizer term in which it can be obtained from the eigenvalue λ_0 which is equal to zero. The correspon-ding eigenvector v_0 is equal to the psf. the standard formula is formulating in which M is data fidelity term where U and R are image regularizers and blur regularizers respectively. The masking (3x3) filter can be [-1 0 1; 0 0 0; 1 0 -1] .This can be used in order to prevent over smoothing of edges and the details in the reconstructed image. Regularization parameter uses isotropic TV norm 1. Ø(x) = ||x||. Consider U and R be the regularization terms for image and blur respectively.

2.2 Blind Deconvolution

Blind deconvolution [15] is an ill posed problem therefore in order to remove blur ill posed problem should be converted in to well posed problem. Coming section explains about ill posed problem. Using regularization ill-posed problem can be converted to well posed problem. Bregman variable splitting can be used to solve this effectively with ALM. Image regularizers using directional priors in x, y, z direction. Therefore it helps to provide the directional view in three directions. The masking filter using (3x3) square matrix. The l_1 and l_2 components can split using split Bregman variable splitting. Consider the equation below in which M is data fidelity term.

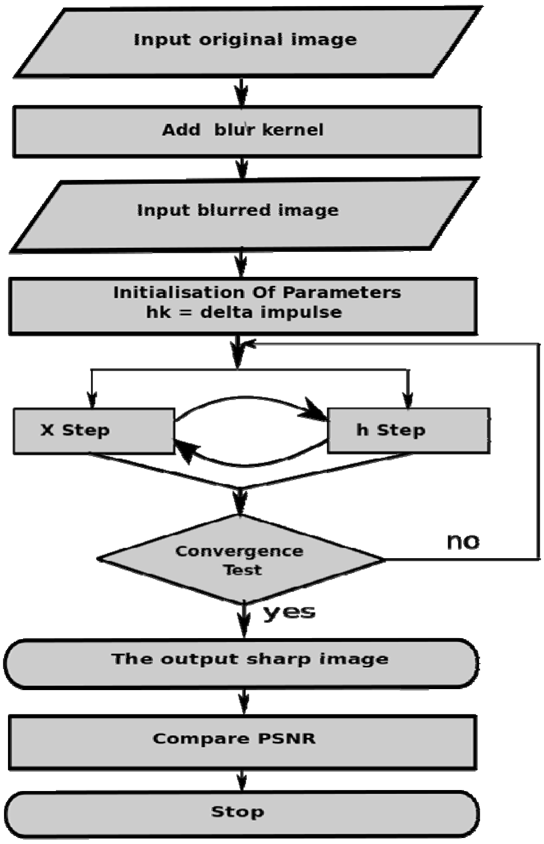

Fig. 1. Flowchart of AM algorithm.

Where U and R are image regularizers and blur regularizers respectively

$$\min_{x,h_k} M(x,h_k)+u(x)+R(h_k) \tag{4}$$

where

$$\text{M}(\text{x}, h_k) = \frac{\lambda}{2}\sum_{k=1}^{k}\|x * h_k - y_k\|^2 \tag{5}$$

where ||.|| denotes l_2 norm.

The overall architecture represented in above figure. The main articrafts that can occur in the images are aliasing and motion due to phase shifts in the sampling and the noise occurred as repetitive pattern. Normalization can be used in order to remove noise effect due to the low contrast in the images. Ringing effect can be removed using edge tapering. Then the blind deconvolution step with Bregman iteration and variable splitting method using Augmented Lagrangian method(ALM). Final step using the non blind deconvolution in order to obtain the deblurred or restored image.

2.3 Basics for Blind deconvolution

Consider the eq (1.1), it can be rewrite as

$$y_k(\text{i}) = (h_k * x)(\text{i}) + w_k(i) \text{ where, } \{1 \le \text{k} \le \text{k}, \text{I} \in N^2 \tag{6}$$

We assume that K > 1 therefore the input images ie,

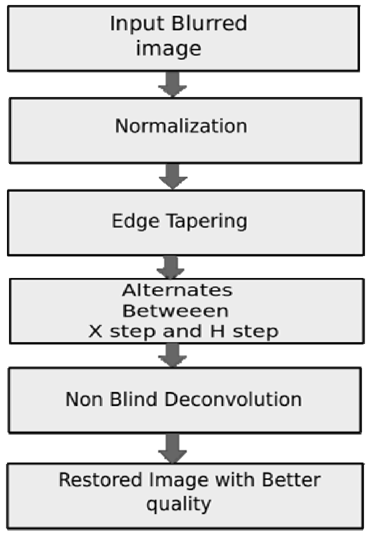

Fig. 2. The Overall Architecture.

blurred noisy image can be y_K Values from [$y_1, y_2, \ldots .. y_k$], $y_k \in R^{n^2}$.

Where h_k represents blur kernel or Point spread function. It is convoluted to the original image. The noise w_k is added to the convoluted term.

The matrix notation be:-

$$y_k = XH_K + w_k \tag{7}$$

Matrices H_k and X obtained by convolving i^{th} element of h_k and x_k, where x(i)=$[x]_i$ for matrix notation

3. Ill posed problem

As this case in which unknowns are not equal to no: of variables, it is called ill posed, and in order to do deconvolution it should be a well posed problem. So here blind deconvolution algorithm is necessary and in order to make it in to well posed, undergoes regularization. Solving using Alternating Minimization Algorithm and variable splitting method it can be split in to two sub optimization problem. Two steps are involved that are (i) x step (ii) h step

$$\text{xstep: } \min_x M(x\ \ h_k)+u(x) \tag{8}$$

$$hstep: \min_{h_k} M(x, \ _k)+i R(h_k) \tag{9}$$

Regularization uses isotropic TV model with norm 1. So that it will not find much difficulty for solving. Regularizer is Ø(x) = ||x||. U and R be the regularization terms for image and blur respectively.

$$\text{U(x)}=\sum_i \Phi((i)) = \sum_i \sqrt{(\nabla_x x(i))^2 + (\nabla_y x(i))^2 + (\nabla_z x(i))^2} \tag{10}$$

Using MC regularization term there is a chance for simultaneously minimizes the energy function respect to both image and blur. The algorithm which used in spatially misaligned images are not suitable here as it will not efficient for large blur and images.

Using Vector matrix notation

$$\mathrm{U(x)} = \Phi\left(D_z(x), D_y(x), D_z(x)\right) = \sum_i \sqrt{[D_z x]_i^2 + [D_y x]_i^2 + [D_z x]_i^2} \tag{11}$$

where D_x, D_y and D_z are Derivatives with respect to x, y and z.

4.OPTIMIZATION PROBLEM

Optimization is considered as hard problem which includes linear and non linear problem. As a result it is a constrained optimization problem and This can be split in to two sub optimization problem(i) x step (ii) h step

Two variables to be solved includes two steps:

1. step 1: fix h and optimize for X

$$x' = \arg\min_x M(h', x) \tag{12}$$

2. step 2: fix x and optimize for h

$$h' = \arg\min_x M(h, x') \tag{13}$$

To verify the result in algorithm:-

1. Function should satisfy two conditions
   (a) Convex function jointly in both h and x.
   (b) Smooth function in both h and x.

2. Conditions to satisfy convergence to global optima.

3. But practically function M is not convex, still this algorithm gives better convergence.

4.1 X step

Steps for x step algorithm:
1. Initialisation of parameters, variables

$$v_x = v_y = a_x = a_y = K = 0$$

2. Set maximum no. of iteration
3. ALM EQUATION

$$L = H^T{}_e G + \left(\frac{\beta}{\lambda}\right)\left[conj\left(FD_z\right).FT\left(a_X + V_x\right)\right] + \left[conj\left(FD_Y\right).FT\left(a_X + V_Y\right)\right]$$

4. FT(x) = L_z / (FT(H^T H) + (β/λ) D^T D, where

$$D^T \mathrm{D} = conj\left(FD_x\right)FD_x + conj\left(FD_y\right)FD_y + 0.0002 conj\left(FD_z\right)FD_z$$

5. Update variables and β=1.22 and λ=1.23
6. k = k +1
7. Convergence test if satisfied, then stop.
8. x value

4.2 h step

Steps for h step algorithm
1. Initialization of parameters, variables

$$v_h = a_h = K = 0$$

2. Set mximum no. of iteration.
3. ALM EQUATION

$$L = \left(\frac{\beta}{\lambda}\right)FT\left(v_h + a_h\right) + \left[conj\left(FT(X_z)\right).FT\left(EG_x\right)\right] + \left[conj\left(FT(X_y)\right).FT\left(EG_y\right)\right]$$

4. FT(h) = L_h / (FT(X^T X) + (β/λ))

   Where, $X^T \mathrm{X} = conj\left(FX_x\right)FX_z + conj\left(FX_y\right)FX_y$
5. Update variables and post zero values outside h support
6. K = k + 1
7. Convergence test if satisfied, then stop.
8. h value

5. Non Blind deconvolution for Image Estimation

Once the h value is known the image estimation can be easily done, here the problem is non blind deconvolution. The image estimation loop with known h value can comes into picture here. Alternating the loop between x step and h step values that can be taken in to the main loop. The stopping criterion can be using

$$\frac{\| h^k - h^{k-1} \|}{\| h^{k} \|} < \text{Tolerance} \Rightarrow \text{for x step}$$

$$\frac{\| x^k - x^{k-1} \|}{\| x^k \|} < \text{Tolerance} \Rightarrow \text{for h step}$$

Initialization of parameters, variables $v_x = v_y = a_x = a_y =$ k = 0 and x^k = 0, at k = 0 and impulse function for h^k and ALM equation as follows:

$$L = H^T{}_e G + \left(\frac{\beta}{\lambda}\right)\left[conj\left(FD_x\right).FT\left(a_X + V_Z\right)\right] + \left[conj\left(FD_Y\right).FT\left(a_X + V_Y\right)\right] \tag{14}$$

$$\mathrm{FT(x)} = \mathrm{L} / (\mathrm{FT}(H^T \mathrm{H}) + (\beta/\lambda) D^T \mathrm{D} \tag{15}$$

where, $D^T D = \text{conj}(F D_x)F D_x + \text{conj}(F D_y)F D_y$ After all iteration the final convergence point meets and the image can be restored efficiently. This image is considered as final reconstructed image.

6. Application

7. Astronomical Image Deblurring

Astrophotography faces lot of challenges due to noise effects and atmospheric conditions. Adaptive regularization method can be used to solve this problem effectively using an algorithm called Alternating minimization. This algorithm which can effectively reconstruct a degraded astronomical image. There are many challenges in this area such as object fading, light effect elimination, distance between the object and sensors called charge coupled devices. Astronomical images[19-22] are mainly close to gray scale image but after capturing the image it undergo either broad band or narrow band filtering. Adaptive Regularization technique using the algorithm Alternating minimization can remove the point spread function and can effectively produce the deblurred image.

8. Medical Image Deblurring

Medical image plays crucial role in order to detect certain diseases and there are certain diseases which cannot detect without this images. The early stages was using X-rays and later Scan images using Ultra sound and CT and MRI also introduced. Xray [11, 12] images are not perfect images as it causes noise and blur. The images as a result called degraded images. The noise can be removed using direct filtering such as Gaussian filter in case of white noise and if Rician noise using non local means filters etc. The blurring can be removed using inverse filtering methods.

Using this algorithm one can effectively reconstruct the degraded medical images. Mainly it is divided in to two steps that is blind deconvolution and non blind deconvolution. The deconvolution is an inverse problem where it is blind as the unknown variables are not equal to the number of equations. This is also known as ill posed problem. Normalization can be used in order to increase the contrast without distorting the relative intensity values of the image. This is also known as contrast stretching.

Here we are using both X ray and ultrasound scan image. There are main articrafts that can occur in the images are aliasing and motion due to phase shifts in the sampling and the noise occurred as repetitive pattern. Normalization can be used in order to remove noise effect due to the low contrast in the images. Ringing effect can be removed using edge tapering. Then the blind deconvolu-tion step with Bregman iteration and variable splitting method [13, 14] using Augmented Lagrangian Me-thod(ALM). Final step using the non blind deconvolution in order to obtain the restored image.

9 RESULTS

9.1 Colour Image Deblurring

To illustrate the minimization properties we have used alternating minimization algorithm. The previous work was using regularization term with 1 D Laplacian kernel and here our estimation using 2 D kernel that includes masking filter of (3x3) that gives directional priors. The adaptive regularization using additional penalty term that is called weight term which gives better results. This is obtained by updating the weight or balance parameters in each iteration step i.e, β = 1:23 and λ = 1:22.

The input image using disaster image fig (3) source: google image of size (256x149) and convolve it with disk blur of radius 4 and psf set for (10x10) matrix. Comparison Table I and II gives the comparison of PSNR using previous method that is regularization and our method adaptive regularization. We can observe that the PSNR for adaptive regularization gives better results. The experiment using different input images that is the lighthouse picture from windows photo viewer sized (1024x186) etc has being used as input image and the comparison is observed. In adaptive regularization we observed that l_p gives better PSNR and better quality than l_2. The results that are improving from previous method and obtained better results using proposed method. Also represented the estimated PSF and the reconstructed image using l_2 and l_p in adaptive regularization method. Table II represents the PSNR for different images in which the iteration sets as 4 and the adaptive regularization is executed and the Table I represents the PSNR for different iteration in regularization method.

The proposed method gives better performance in estimation of blur and to obtain the deblurred image. This method can be well executed in case of general blurs that can be occurred due to atmospheric condition and also due to the distance between the camera and the image.

10 CONCLUSION

The main focus of this paper is to improve the quality of the image using an algorithm proposed by Filip and Peyman. Here we are using the directional priors and the masking using (3x3) filter and comparison of PSNR for Lp and L2 norm. Regularization using penalty weighted term along with image regularizer called adaptive regularization, this gives improvement in the PSNR value of the restored image. The proposed method is very well performed here and that can be observed from the comparison table I and II. This work proposes the image deblurring using MC blind deconvolution via Alternating Minimization Algorithm. Lp norm along with adaptive regularization gives better results than L2 norms. This algorithm suites very well as it can effectively solve for two variable unknowns. As two variables are unknown it becomes indirect solution method and it uses the Bregman iteration

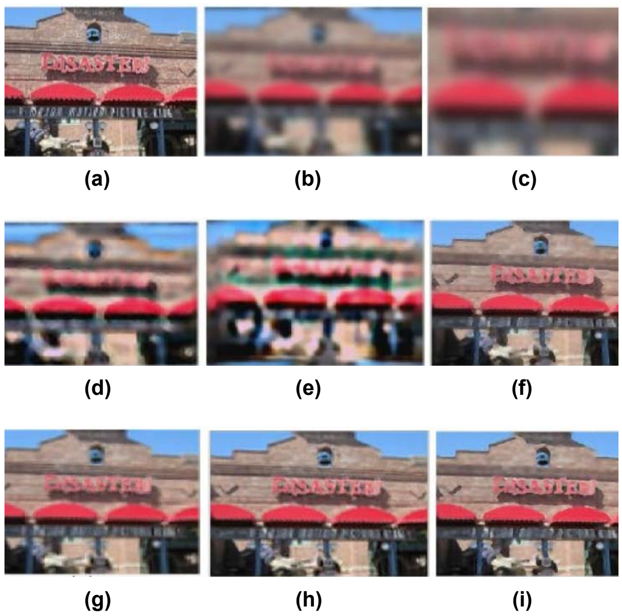

Fig. 3. Comparison using previous result and our method (a) input image used is google image of size(259x194)(b)blurred image (c) the extracted portion which require more quality (d) using l2norm (e) using lp norm (f) using l2regularization and directional priors (g)using lp regularization and directional priors (h)using adaptive regularization lp norm (i)using adaptive regularization l2.

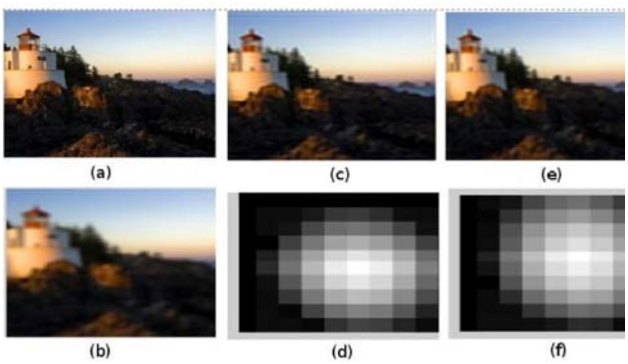

Fig. 4. The restored image using adaptive regularization with lp and l_2 (a)input light house image (b)the blurred image using disk blur (c)result using l_2 and (d)result using l_p norm (d) shows the psf corresponding to (c) and (e) shows the psf corresponding to (d).

along with ALM equation to solve this. The ill posed problem can be solved using regularization adaptively so that additional weight or penalty to improve the performance and also the masking filter of (3x3) matrix and 2D Laplacian kernel. The directional prior which uses 3 directions such as x, y and z. The adaptive regularization using additional penalty term that is called weight term which gives better results. This is obtained by updating the weight or balance parameters in each iteration step i.e, β = 1:23 and λ = 1:22. This method can be simulated using MATLAB software. The resultant PSNR value can be compared with the previous work to analyse the quality of the image after deblurring.

Table 1. Comparison of PSNR for different iteration.

Adaptive Regularization using Directional Priors

Input Image	MSE		PSNR(L2)			MSE		PSNR (Lp)		
	min	max	Channel 1	Channel 2	Channel 3	min	max	Channel 1	Channel 2	Channel 3
disaster	61.4	62.9	30.1428	30.2448	30.2327	62.9	64.9	30.0081	30.2448	30.1381
koala	59.7	60.1	30.3404	30.3691	30.3359	47.5	49.0	31.3599	31.3444	31.2240
tulips	17.9	45.1	31.6275	31.5799	35.5895	17.8	43.1	31.8164	31.7855	35.6053
penguins	25.4	30.9	34.0767	33.7449	33.2274	26.3	30.9	33.9189	33.6989	33.2274
Lighthouse	20.7	24.7	34.2026	34.6261	34.9561	20.1	23.5	34.4193	34.7974	35.0895
Jelly fish	17.9	45.1	34.8523	35.5240	34.0147	17.8	43.1	34.9327	35.6895	34.6918

(a) The comparison between regularized restored image and original image using l2 and lp norm for different iteration.

Table 2. Comparison of PSNR for different images.

Regularization using Directional Priors

No of iterations	MSE		PSNR(L2)			MSE		PSNR (Lp)		
	min	max	Channel 1	Channel 2	Channel 3	min	max	Channel 1	Channel 2	Channel 3
2	15.3	40.7	32.0402	32.0250	36.2625	16.5	40.3	32.1595	32.0764	35.9394
3	14.6	39.7	32.1951	32.1395	36.4635	15.1	37.1	32.0764	32.4341	36.3309
4	15.2	38.8	32.2604	32.3285	36.3298	14.4	33.3	35.9394	32.9201	36.5365

(a) The comparison between adaptive regularized restored image and original image using $l_2$andl_p norm with different input images.

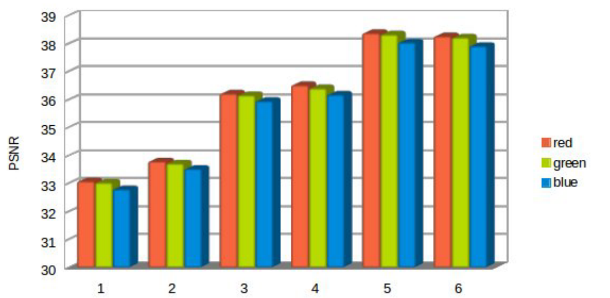

Fig. 5. Graphical representation Of PSNR in Medical image.

The above graph represents the PSNR values for three channels that are red, green blue channel respectively using different.

Iteration from 1 to 6.

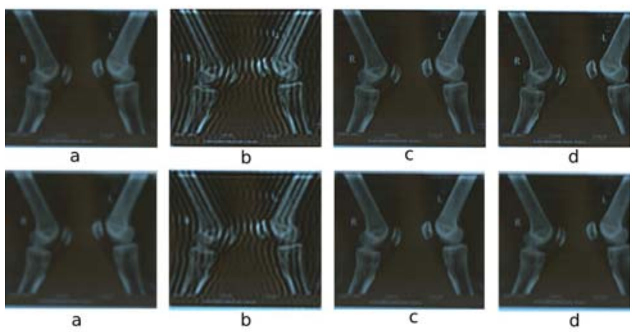

Fig. 6. The reconstructed X ray images using lp adaptive regularization method. The top figures shows debluring from blur kernel Gaussian (a)blurred input image (b)1 step iteration (c)3 step iteration (d)6 step iteration. The bottom figures using (a)disk blurred input image (b), (c), (d)for 1, 3, 6 step iteration results.

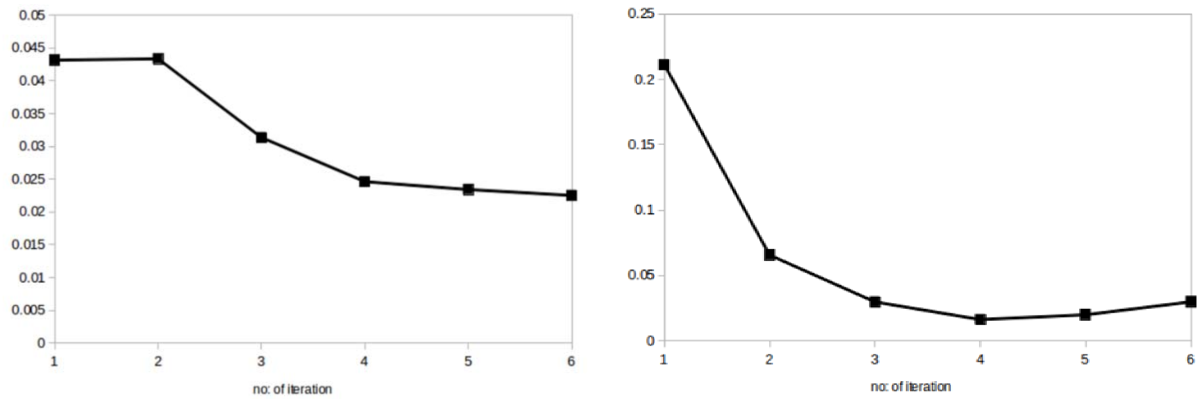

Fig. 7. The top graph represents the blind x step convergence and bottom shows the h step conver-gence for 6 step iteration.

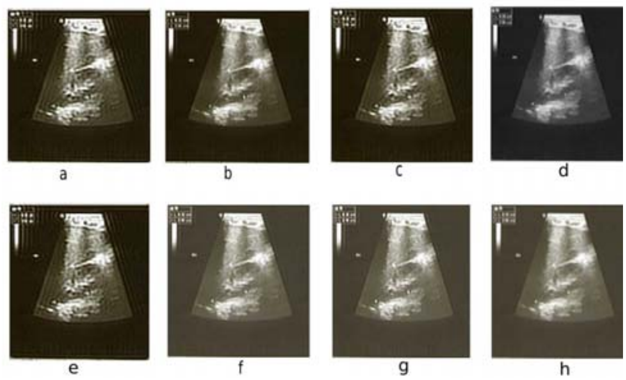

Fig. 8. This represents restoration of image using lp adaptive regularization. Top layer shows blind deconvolution results. (a)result for 1 step iteration (b)4 step iteration (c)5 step iteration (d)6 step iteration. The bottom results shows the non blind deconvolution (e), (f), (g), (h) for 1, 4, 5, 6 step iteration respectively.

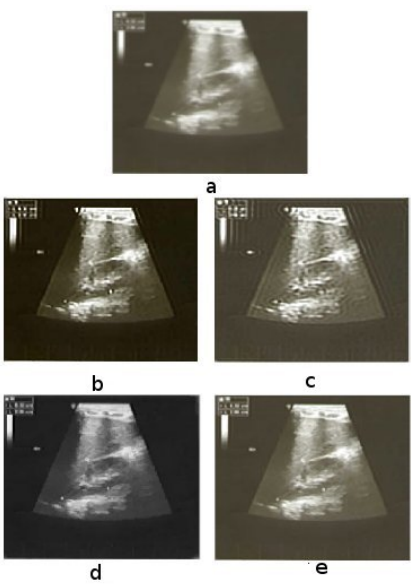

Fig. 9. Restoration of scan image using adaptive regularization (a)the input blurred image (b) and (c)using l_2 norm blind and non blind deconvolution (d) and (e)represents the l_p norm blind and non blind deconvolution.

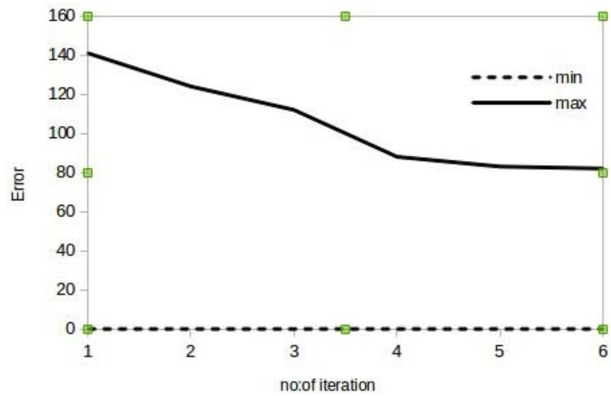

Fig. 10. Mean Square Error Graph using lp norm adaptive Regularization.

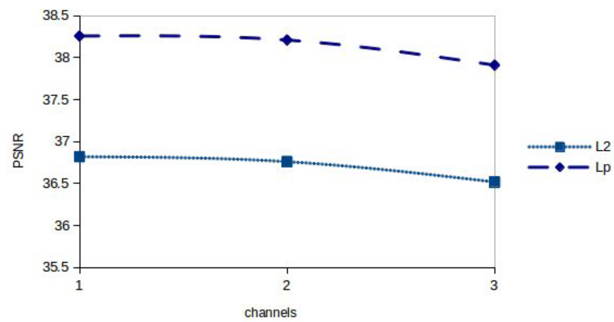

Fig. 11. Graphical representation for medical images.

The above graph represents the result for l2 and lp norm adaptive regularization.

set the minimum switching coefficient β to 5, the RTT-based scheme will allow MT to switch its primary path at 51seconds because1.84 $\geq$ 5·0.33(=1.65). However, this aggressive switching requires CT to reset its *cwnd*. Unfortunately, the switched primary path experiences a sudden RTT peak at 56 seconds, which indicates the overall throughput is limited using the RTT-only scheme. On the other hand, our proposed scheme delays this path switching to 60 seconds when the historical RTT condition is satisfied for recent δ(=5) consecutive measurement steps.

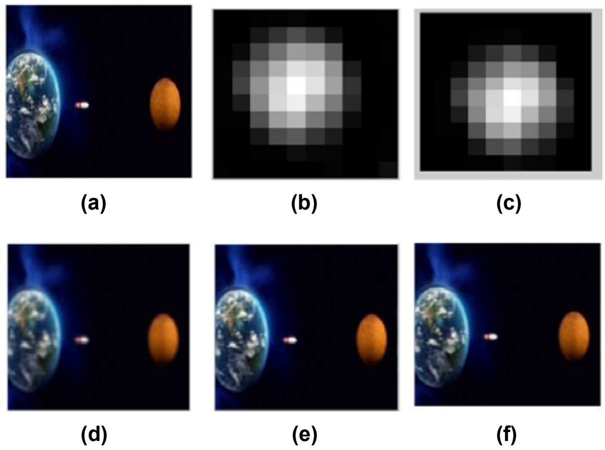

Fig. 12. The blind and non blind deconvolution results (a)The input image (d) The blurred image (b) and (e)The blind deconvolution results for PSF and image respectively (c)and (f)non blind deconvolution results for PSF and image respectively.

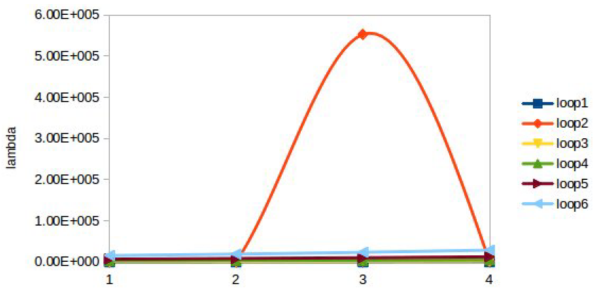

Fig. 13. Graphical Representation of the update parameter λ used in adaptive regularization.

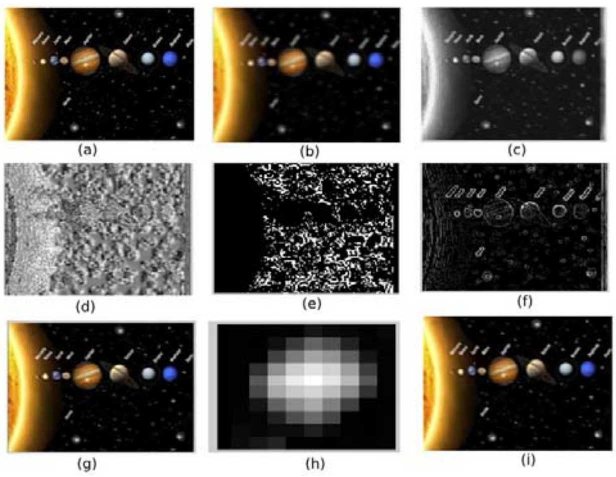

Fig. 14. Directional Priors. (a) input image used is google image source: skymetwhether.com of size(264x191) (b)blurred image (c)gray scale reconstructed image (d)details in x direction (e)details in y direction (f)details in z direction (g)blind deconvolution resultant image (h) Final(a) input image used is google image source: skymetwhether.com of size(264x191) (b)blurred image (c)gray scale reconstructed image (d)details in x direction (e)details in y direction (f)details in z direction (g)blind deconvolution resultant image (h) Final PSF (i)non blind resultant image.

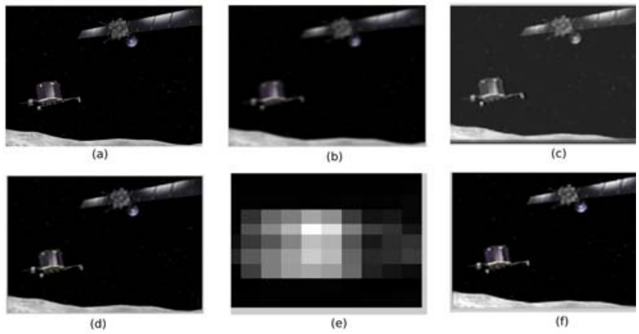

Fig. 15. Restoration of astronomical image using adaptive regularization (a)the input image source: Rosetta and Philae at comet node full image.jpg of size(625x428) (b)blurred image (c)gray scale reconstructed image (d)blind deconvolution reconstructed image (e)final PSF (f)non blind deconvolution reconstructed image.

We can also observe that the alternative path shows steady RTT after the primary path has explicitly failed at 66 seconds. More importantly, this delayed switching affects the throughput since it allows both CT and MT to continuously increase or maintain their *cwnd* rather than restarting at the slow-start phase. In our experiment, we put the different weight

References

[1] Filip Sroubek, Member IEEE and Peyman Milanfar, Fellow IEEE "Robust Multichannel Blind Deconvolution Using Alternating Minimization Algorithm". IEEE Transactions on Image Processing, Vol. 21, No. 4, APRIL 2012.

[2] G. Ayers and J. C. Dainty, Iterative blind deconvolution method and its application, Opt. Lett., vol. 13, no. 7, pp. 547-549, Jul. 1988.

[3] T. Chan and C. Wong, Total variation blind deconvolution, IEEE Trans. Image Process., vol. 7, no. 3, pp. 370-375, Mar. 1998.

[4] R. Molina, J. Mateos and A. K. Katsaggelos, Blind deconvolution using a variational approach to parameter, image, and blur estimation, IEEE Trans. Image Process., vol. 15, no. 12, pp. 3715-3727, Dec 2006.

[5] Blind Image Deconvolution, Theory and Application, P. Campisi and K. Egiazarian, Eds. Boca Raton, FL: CRC Press, 2007.

[6] Definitions and examples of inverse and ill-posed problems S. I. Kabanikhin Survey paper.

[7] Yilun Wang, Junfeng Yang, Wotao Yin, Yin Zhang. A new Alternating minimization algorithm for total variation image Reconstruction.

[8] G. Panci, P. Campisi, S. Colonnese and G. Scarano, Multichannel blind image deconvolution using the bussgang algorithm: Spatial and multiresolution approaches, IEEE Trans. Image Process., vol. 12, no. 11, pp. 1324-1337, Nov. 2003.

[9] F. Sroubek and J. Flusser, Multichannel blind deconvolution of spatially misaligned images, IEEE Trans. Image Process., vol. 14, no. 7, pp. 874-883, Jul.

2005.
[10] L. Rudin, S. Osher and E. Fatemi, Nonlinear total variation base noise removal algorithms, Phys. D, vol. 60, no. 14, pp. 259-268, Nov. 1992.
[11] G N Sarage and Dr Sagar Jambhorkar Enhancement of chest Xray images using filtering techniques.
[12] Rinku Kalotra and Anil Sagar. A novel algorithm for blurred image rest in field of medical image.
[13] T. Goldstein and S. Osher, The split bregman method for l_1 regularized problems, SIAM J. Imag. Sci. vol. 2, no. 2, pp. 323-343, Apr. 2009.
[14] J. Miskin and D. J. MacKay, Ensemble learning for blind image separation and deconvolution, in Advances in Independent Component Analysis, M. Girolani, Ed. New York: Springer-Verlag, 2000.
[15] A. Levin, Y. Weiss, F. Durand and W. Freeman, Understanding and evaluating blind deconvolution algorithms, in Proc. IEEE Conf CVPR, 2009, pp. 1964-1971.
[16] G. Harikumar and Y. Bresler, Perfect blind restoration of images blurred by multiple filters: Theory and effecient algorithms, IEEE Trans. Image Process., vol. 8, no. 2, pp. 202-219, Feb. 1999.
[17] G. Giannakis and R. Heath, Blind identi_cation of multichannel FIR blurs and perfect image restoration, IEEE Trans. Image Process., vol. 9, no. 11, pp. 1877-1896, Nov. 2000.
[18] M. V. Afonso, J. M. Bioucas-Dias and M. A. T. Figueiredo, Fast image recovery using variable splitting and constrained optimization, IEEE Trans. Image Process., vol. 19, no. 9, pp. 2345-2356, Sep. 2010.
[19] Zohair AlAmeen, Dzulkii Mohamad, MohdShafry M. R and Ghazali Sulong Restoring Degraded Astronomy Images using a Combination of Denoising and Deblurring Techniques International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 5, No. 1, March, 2012.
[20] G. Landi, E. Loli Piccolomini A projected Newton-CG method for non negative astronomical image de-Blurring.
[21] Elena loli piccolomini, Scaling techniques for gradient projection-type methods in astronomical image Deblurring.
[22] R. C. Puetter, T. R. Gosnell and Amos Yahil Digital Image Reconstruction: Deblurring and Denoising Annual Review of Astronomy and Astrophysics Vol. 43: 139-194 Volume publication date August 2005.
[23] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis and W. T. Freeman, Removing camera shake from a single photograph, in Proc. Siggraph: ACM Siggraph Papers, New York, 2006, pp. 787-794.

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