Image Restoration using ADMM-TV Algorithm

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Abstract— *ADMM (The alternating direction method of multipliers is being used now a days to solve the problem of image restoration. The ADMM splits the inverse problem into small fragments. In this paper we make the use of ADMM TV algorithm to reconstruct the distributes parameters. In each iteration an operator splitting is put into action to simplify the treatment of TV regularizes avoiding smooth estimation resulting into move efficient variant of ADMM.*

Keywords— ***Balanced regularization, image restoration, ADMM TV .***

I. INTRODUCTION

Image restoration is an inverse problem. The objective is to restore the original image, Which is mingled with some noise, the mathematical model is ,

$$Y= Bu+ n \qquad (1)$$

Where $Y\varepsilon R^m$, B is a linear, $u\varepsilon R^n$,is deconvolution operator. The current paper makes use of the ADMM B algorithm to solve the regularization problem in the image restoration. The problem is modelled by splitting :

$$\min_{x, v\varepsilon R^2} \frac{1}{2}\| BWx - y\|_2^2 + \frac{\gamma}{2}(I - W^T W)x\|_2^2 + \lambda T\ |v|_1 \quad (2)$$

subject to $x = v$.

Define

$$f_1(x) = \frac{1}{2}\|BWx - y\|_2^1 + \frac{\gamma}{2}\ \|(I - W^T W)x\|_2^2 \qquad (3)$$

and

$$(v) = \lambda^T\ |v|_1 \quad , \qquad G = I. \qquad (4)$$

The objective of image restoration is to remove defects and replace the detoriation with some improvements in an image. The main causes of distortions are motion blur, noise, and camera misfocus. In cases like motion blur, it is possible to come up with an very good estimate of the actual blurring function and compensate the blur to restore the original image. In cases where the image is corrupted by noise, the best we may hope to do is to undo the degradation . In this project, we will introduce and implement several of the methods used in the image processing world to restore images.

II. RELATED WORK

shoulie xie[1] makes the use of ADMM to solve the balance regularization problem(2) in frame based standard image restoration. The problem is further stated as under equation(2),(3) and (4)If the ADMM is applied then we get the following linear system.

$$x_{k+1} = [W^T B^T BW + \gamma\ (I - W^T W) + \mu I$$

Denotes the regularized version of Hessian matrix $W^T B^T BW$.

Algorithm ADDM for balance Regularization Approach (ADDM-B)

1) Set $k = 0$, choose $\mu > 0$, v_0 and $d0$;
2) *repeat*;
3) $r_k = W^T B^T y + \mu(v_k + d_k)$;
4) $x_{k+1} = \frac{1}{\mu}(\alpha r_k + (1 - \alpha)W^T W_{rk} - W^T F W_{rk})$;
5) $v_{k+1} = \text{soft}(v\_k , \frac{\lambda}{\mu})$;6) $d_{k+1} = d_k - (x_{k+1} - v_{k+1})$;
7) $k \leftarrow k + 1$;
8) *until stopping criterion is satisfied.*

III. PROPOSED WORK

In this paper the proposed Algorithms is as under:

1) Read Gray Image as an N*N size.
2) Apply Gaussian blur or Uniform Motion blur with noise variance is 0.00001 and mean is zero.
3) The total variation regularization approach can be formulated as

min (bu/2) || FW - k ||_1 + ||W||_ADMMTV as ||W||_ADMMTV = sqrt (m||DxW||^2 + n||DyW||^2 o||DtW||^2)

,

where F is point spread function, bu is total variation regularization parameter, k is input image and W is initial variable for k. The first term denotes penalty on the data fidelity, the last term penalizes the sparsity of coefficient vector, the second term penalizes the distance between the frame coefficients *W* and the range of *WT*, i.e., the distance to the canonical frame coefficients of *u*.

4) Using the classical augmented Lagrangian (AL) approach, also known as the method of multiplier (MM), to deal with the problem , we can obtain the following iterative algorithm

DxW = W(x+1,y, t) - W(x,y,t)

DyW = W(x,y+1, t) - W(x,y,t)
DtW = W(x,y, t+1) - W(x,y,t)
This leads to the so-called alternating direction method of multipliers (ADMM)
5)Compute Fourier Transform:
rhs = fftn ((bu/rho)*H + Dt (u1-(1/rho)*s1, u2-(1/rho)*s2, u3(1/rho)*s3));
S where rhs is fourier coefficient, u1,u2,u3 are penalty parameters, Dt is complex conjugate and s1,s2,s3 are lagrange multiplier for DW1,DW2,DW3 set to 0
6) Calculate balanced minimization problem
v = sqrt (v1.^2 + v2.^2 + v3.^2)
Where v1,v2,v3 are v1 = DW1+(1/rho)*s1,v2 = DW2+(1/rho)*s2,v3 = DW3+(1/rho)*s3
7) Calculate Improve Signal Noise ratio, Mean square error and signal noise ratio of original image and restored image.

III. RESULT

Table and Figure Our base paper work table1:

	Uniform blur base		Gaussian blur	
Image	PSNR	MSE	PSNR	MSE
Baboon	67.69	0.0112	68.055	0.010
Cameraman	67.90	0.0105	73.24	0.0031
Leena	69.81	0.002	73.39	0.0030
Barbara	67.908	0.0105	69.10	0.0080
Peeper	73.59	0.0028	76.701	0.0014

Our proposed work table2:

	Uniform blur		Gaussian blur	
Image	PSNR	MSE	PSNR	MSE
baboon	69.771	0.007	67.865	0.011
cameraman	76.221	0.002	71.606	0.004
leena	74.322	0.002	70.854	0.005
barbara	69.632	0.007	68.066	0.010
peeper	77.999	0.001	73.923	0.003

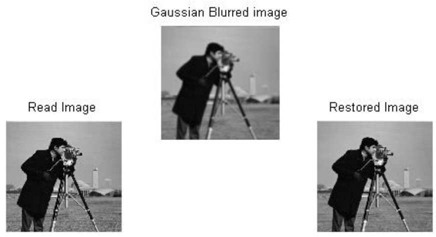

fig a **fig b** **fig c**

Fig1. Image deblurring. (a) Original cameraman image. (b) Gaussian blurred image. (c) Restored image using ADMMTV filter.

V. CONCLUSION

The results obtained by implementing ADMMB and ADMMTV algorithm are enumerated as above the proposed results reveal that the images with higher motion blur are restored with better quality. The higher PSNR and lesser MSE values prove that technical proposed ensures better methodology and satisfactory image restoration. Our proposed results give better results in comparison to base results on basis of PSNR and MSE value. It decreases the uniform and Gaussian blur of an original image.

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