Regularized Deblurring using Directional Prior with Sparse Representation

Subhajit Dhar, Vivek Maik, Mayank Srivastava

Abstract : Blind deconvolution defined as simultaneous estimation and removal of blur is an ill-posed problem that can be solved with well-posed priors. In this paper we focus on directional edge prior based on orientation of gradients. Then the deconvolution problem is modeled as L2-regularized optimization problem which seeks a solution through constraint optimization. The constrained optimization problem is done in frequency domain with an Augmented Lagrangian Method (ALM). The proposed algorithm is tested on various synthetic as well as real data taken from various sources and the performance comparison is carried out with other state of the art existing methods.

Keywords: Deblurring, Restoration, Sparse .prior, gradient angle prior.

I. INTRODUCTION

Recent increases in screen resolution of cameras, camcorders, and television has increased the need for image pre-processing in the form of high dynamic Range (HDR), color enhancement imaging (CEI), contrast enhancement and blur restoration. Out of these blur restoration offers the most difficult challenge as the solution finding is not direct and comes as in the form of an ill-posed problem. The ill-posed problem can be represented as

$$y = H * x + n \qquad (1)$$

Here *y* is the blurred imaging, *H* is the blur kernel or point spread function (PSF) matrix and *n* is the additive noise. Typically, in any image restoration given *'y'* we have to find *H*, *x* and n which represent the unknown and 'y' represent the single known variable in the equation, so for finding 3 unknown variables a well-posed problem requires minimum use of atleast 3 equations. But here we have just single equation given in (1) which makes it an ill-posed problem. The ill-posed problem like the one above requires the use of mathematical methods known as optimization methods. In this paper we model the above given ill-posed problem as one such optimization method and solve it as

$$\underset{x}{argmin}\|y\text{-}Hx\|^2 + \lambda\|Cx\|^2 \qquad (2)$$

The above equation known as L_2*-regularized minimization* approach where the minimization happens for variable *x*. Through this minimization process we try to separate the variables H and x which otherwise appear as the convolution product (*) in equation (1). The above equation when minimized for *x* we will get *H* which when applied to *y* we will get imaging inverse solution.

The parameter λ and *C* represent the regularization parameter and high pass filter convergence of the algorithm.

There are various ways to enhance the abovementioned conventional approach. In this paper we propose the use of directional gradient orientation where the minimization process is controlled by weights decided according to the magnitude and direction of the gradient. This will give variation restoration which preserves edges better at different region decided by the gradient information at that particular location. The major contribution of the proposed deblurring algorithm can be listed as (i) Use of directional prior as constraint in the regularized optimization (ii) Use of alternating minimization to solve for *H* and *x*, (iii) Use of penalty function as Bregman variables and Augmented Lagrangian for faster and better convergence. The rest of the paper is organized as follows : Section II explains the proposed algorithm, Section III explains noise in deblurring, Section IV explains Figures and Values, Section V explains the experimental results and Section VI concludes the paper.

II. PROPOSED METHODOLOGY

The image deconvolution / deblurring problem as optimization model described above is usually operated in the frequency domain as in frequency domain the convolution operation (*) become multiplication in frequency and eases up on the computation process. The image deblurring also known as the deconvolution is the reverse of convolution where we separate the convolved variables H and x thereby separating the blur from the original sharp image. The end product of typical deblurring has estimated input sharp image and blur kernel as shown in (3). The deblurring does its best to remove the mathematical operators connecting *H, x* and *n* and give them as separate variables.

$$y = H * x + n = H, x, n \qquad (3)$$

where *H* denotes an unknown blur or kernel or point spread function which usually smaller in size (3x3 to 13 x 13) in our approach and *n* is the additive noise in the observation.

Operator $*$ stands for linear time domain convolution operator which includes shifting, multiplying and addition of H and x. If we approximate H to some value, we can deconvolve the image using

$$x = H^{-1} y \qquad (4)$$

Where x, H, y denotes frequency domain operators.

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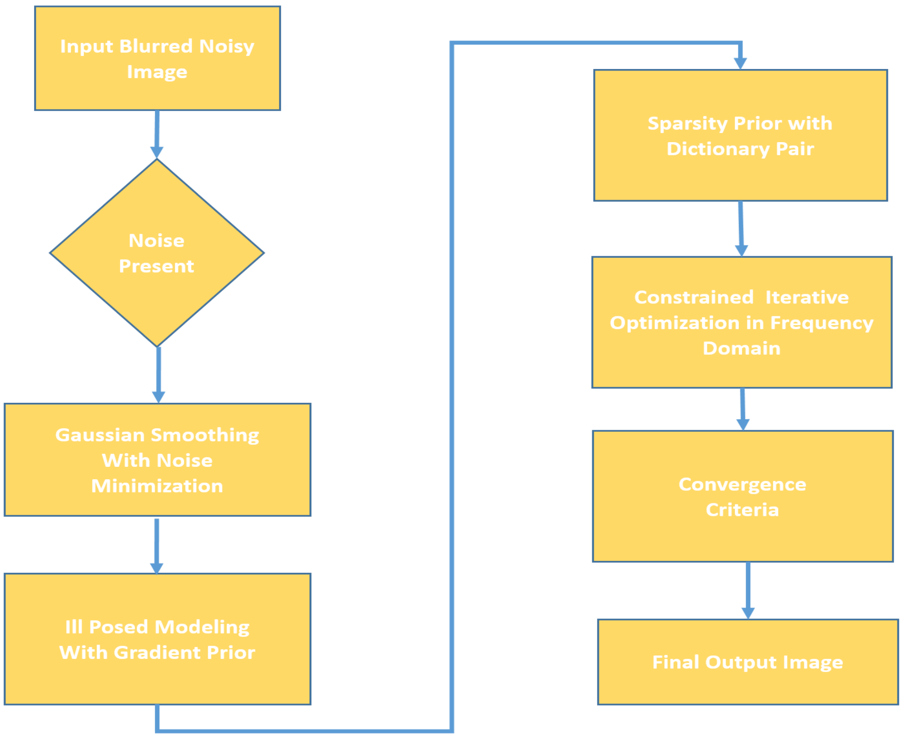

Fig.1. Block Diagram of the Proposed Deblurring Algorithm

The above solution is also not fixed because the inverse of a matrix doesn't exist always and step the results of deconvolution would be better if *H* can be approximated in multiple steps. There we propose a multi-step deconvolution in multiple steps using directional gradient prior mathematically. The directional gradient is seamlessly integrated in to the least square optimization algorithm given in (2) and is solved iteratively with the directional gradients also contributing at each iteration. Using that we can approximate the solution as

$$\hat{x} = \| y - Hx \|^2 + \lambda \| \nabla xy \|^2 \quad (5)$$

where λ is the regularization term that controls to certain extent the degree of blurring thereby preserving the edges and smooth region. In this paper we boost the regularization performance with directional gradient as given in (5). Typical approaches used regularization parameters on a high frequency contents of the image but replacing it with gradient has given us better performance.

The inverse problem can be solved better by adopting direction prior regularization and multi-step H estimation.

$$min \| y_k - H_k x \|_2^2 \quad (6)$$

Once the regularization term is modified with the gradient priors our next major contribution was to split the minimization step in (6) in to two step minimization problem. Using this two-step minimization, we keep two sets of control parameter that will be used consecutively but the first set of parameter controls the x variable and the second set of parameters controls the H parameter. The approach we call it as two step minimization problem. The above minimization term represents multistep optimization problem. For multistep optimization we have to do it with alternating minimization for *H* and *x*. Since *H* and *x* are unknown for each step the value of *H* and *x* are modified alternatively along with other parameters.

$$x-step \min_{x} \{F\{x\}, V\{H\}\} + Q(x) \quad (7)$$

$$H-step \min_{H} \{F\{x\}, V\{H\}\} + R(x) \quad (8)$$

Here $Q(x)$ and $R(h)$ represent the Bregman Variables. The global minimum of the above problem can be solved efficiently by also incorporating the Lagrangian penalty function as Augmented Lagrangian Variable given by

$$\|y - Hx\|_2^2 + \sum_{n=1}^{M} \lambda_n \|\nabla_{\theta_n} - p_n\|^2 \quad (9)$$

where the summation term represent the number of gradient angles used. The proposed approach made use of 5 angles [0, 45, 90, 135,180] in the given order and p_n represent the respective Augmented Lagrangian penalty terms. Through experimental trials it was observed that keeping separate value for the regularization with each angle gave better Signal to Noise Ratio (SNR) improvements that keeping an single regularization term for all the gradient angles. The values of the regularization was chosen in such a way that the gradients in horizontal (0^0), vertical (90^0) and diagonal (45^0) were given more weightage as these edge details are more prominent in most of the cases. The other 2 angles were given weightage towards the latter part of the iterative minimization.

The regularization part in (9) can be worked better by introducing sparse prior along with gradient prior. The sparsity prior in L_2 norm will make sure the deblurred image don't have any speckle noise which is usually very prominent with more number of iterations or excessive optimization. Since the convergence on the iterative optimization for H and x is not always guaranteed and more than often the algorithm stops after a predefined number of iterations. When this happens at times the deblurring will lead to speckle noise which can be overcome by introducing sparsity prior to the above deblurring with gradient prior.

$$D_\alpha [\|y - Hx\|_2^2 + \sum_{n=1}^{M} \lambda_n \|\nabla_{\theta_n} - p_n\|^2] \qquad (10)$$

where D_α represent the dictionary sparsity prior which will in introduced to *H* and *x* during optimization. This dictionary sparsity prior acts more like a noise filter by getting rid of high frequency spots / speckles that get introduced during the minimization process.

III. NOISE IN DEBLURRING

In the above section we proposed a sparsity prior which helps in getting rid of high frequency speckles which get introduced during deblurring. But from (1) we have additive noise *n* which also could affect the noise in deblurring. The algorithm classifies the image as either noisy or noiseless and the algorithm will perform the optimization in two steps as shown below. In the presence of noise, we assume a given distribution for the noise formation.

$$y = H * x + n \qquad (11)$$

In the presence of noise n, the above algorithm works the same except we need to do pre-processing to take care of the noise for H and x of size M X N. In this paper we use a simple noise reduction method which use Gaussian smoothing to suppress the noise and then later this Gaussian smoothing is removed in the iterative deblurring stages. Then the deblurring model is given by

$$\arg\min_x (\|y - H * x\| * G_k - \|y - H * x\|) \qquad (12)$$

In the above equation G_k represents the Gaussian smoothing kernel and $\|y - H * x\|$ represents the noise n. The minimization of 15 will take care of any small noise present in the input image initially prior to the deblurring. As the focus of this paper is deblurring we have not explored this area in detail.

IV. FIGURES & VALUES

Fig. 2 : The experimental results of the proposed algorithm compared with various other methods [3], the PSNR values for images (From top: method1 PSNR=27.45dB, method2 PSNR= 25.32dB, method 3 PSNR=26.56dB, reconstructed image using proposed method PSNR 30.12dB)

Fig. 3 : Real data set with experimented results. (a) captured image, (b) blurred image, (c) noisy image, (d) proposed algorithm result.

V. EXPERIMENT RESULTS – TABLES

Although image contents vary from image to image in order to demonstrate convergence properties of the proposed algorithm, the PSF estimates with respect to the Peak Signal to Noise Ratio (PNSR) and Structural Similarity Index (SSIM) of images. The blurred image compares the quality and standard values to systematic results. The PSF results compared with the estimated results for better deblurred images. We experimented two sets of data sets. The first data set were blurred using Uniform simulated blur and the second data set were blurred using Gaussian blur. For both blur noise variance of $\sqrt{2}$ was used. Figs 2 and Fig 3 show the image results of the proposed algorithm on captured image. Table I to IV show the PSNR and SSIM comparison result of the proposed method with standard state of the art methods such as FISTA, L0-SPAR, IDD-B3D, ASDS-REG, NCSR for various images available as open source dataset. The entire coding simulation was done in MATLAB platform.

TABLE I : PSNR COMPARISON BETWEEN VARIOUS ALGORITHMS: FISTA [12], L0-SPAR [10], IDD-BMD [09], ASDS [11] WITH PROPOSED METHOD FOR UNIFORM BLUR OF 9X9 SIZE WITH NOISE VARIANCE OF $\sqrt{2}$ FOR ONE SET OF IMAGES

	Butterfly	Boats	Cameraman	House	Parrot	Lena	Barbara	Starfish	Peppers	Leaves
FISTA	28.37	29.04	26.82	31.99	29.11	28.33	25.75	27.75	28.43	26.49
L0-SPAR	27.1	29.86	26.97	32.98	29.34	28.72	26.42	28.11	28.66	26.3
IDD-BM3D	29.21	31.2	28.56	34.44	31.06	29.7	27.98	29.48	29.62	29.38
ASDS-Reg	28.7	30.8	28.08	34.03	31.22	29.92	27.86	29.72	29.48	28.59
Proposed	29.1	30.8	28.56	35.1	31.8	30.1	28.1	30.2	29.78	29.2

TABLE II : PSNR COMPARISON BETWEEN VARIOUS ALGORITHMS: FISTA [12], L0-SPAR [10], IDD-BMD [09], ASDS [11] WITH PROPOSED METHOD FOR UNIFORM BLUR OF 9X9 SIZE WITH NOISE VARIANCE OF $\sqrt{2}$ FOR ANOTHER SET OF IMAGES

	Butterfly	Boats	Cameraman	House	Parrot	Lena	Barbara	Starfish	Peppers	Leaves
FISTA	30.36	29.36	26.81	31.5	31.23	29.47	25.03	29.65	29.42	29.36
L0-SPAR	30.73	31.68	28.17	34.08	32.89	31.45	27.19	31.66	29.99	31.4
IDD-BM3D	29.83	30.27	27.29	31.87	32.93	30.36	27.05	31.91	28.95	30.62
ASDS-Reg	29.83	30.27	27.29	31.87	32.93	30.36	27.05	31.91	28.95	30.62
Proposed	30.21	30.94	28.2	32.12	33.67	31.02	28.14	32.65	29.48	30.94

TABLE III : SSIM COMPARISON BETWEEN VARIOUS ALGORITHMS: FISTA [12], L0-SPAR [10], IDD-BMD [09], ASDS [11] WITH PROPOSED METHOD FOR GAUSSIAN BLUR OF 9X9 SIZE WITH NOISE VARIANCE OF $\sqrt{2}$ FOR ONE SET OF IMAGES

	Butterfly	Boats	Cameraman	House	Parrot	Lena	Barbara	Starfish	Peppers	Leaves
FISTA	0.9119	0.8858	0.8627	0.9017	0.9002	0.8798	0.8375	0.8775	0.8813	0.8958
L0-SPAR	0.8879	0.9094	0.8689	0.9225	0.9262	0.9063	0.8691	0.8951	0.9066	0.8776
IDD-BM3D	0.9287	0.9304	0.9007	0.9369	0.9364	0.9197	0.9014	0.9167	0.92	0.9295
ASDS-Reg	0.9053	0.9236	0.895	0.9337	0.9306	0.9256	0.9088	0.9208	0.9203	0.9075
Proposed	0.9145	0.9562	0.924	0.9564	0.9417	0.9356	0.921	0.9348	0.9423	0.9186

TABLE IV : SSIM COMPARISON BETWEEN VARIOUS ALGORITHMS: FISTA [12], L0-SPAR [10], IDD-BMD [09], ASDS [11] WITH PROPOSED METHOD FOR GAUSSIAN BLUR OF 9X9 SIZE WITH NOISE VARIANCE OF $\sqrt{2}$ FOR ANOTHER SET OF IMAGES

	Butterfly	Boats	Cameraman	House	Parrot	Lena	Barbara	Starfish	Peppers	Leaves
FISTA	0.9452	0.9024	0.8845	0.8968	0.929	0.9011	0.8415	0.9256	0.9057	0.9393
L0-SPAR	0.9442	0.9426	0.9136	0.9359	0.9561	0.943	0.8986	0.9496	0.9373	0.9512
IDD-BM3D	0.9126	0.9064	0.8637	0.8978	0.9576	0.9058	0.8881	0.9491	0.9039	0.9304
ASDS-Reg	0.9381	0.9371	0.9078	0.9333	0.9587	0.9389	0.9088	0.9551	0.9331	0.9508
Proposed	0.9415	0.9463	0.9154	0.9478	0.9652	0.9438	0.9184	0.962	0.9414	0.9586

VI. CONCLUSION

Through this work we have proposed an image deblurring algorithm with the following contribution:

Use of sparsity prior, use of gradient angle prior, Lagrangian penalty with Bregman variables for better convergence, effective treatment of noise in the given ill posed equation. This method gives stability of image restoration by directional priori information. The sparse representation based upon PSNR estimated values under the assumption of SSIM results. The performance of the algorithm was found to be same as or better than some of the standard established algorithms found in recent literature. One drawback that was found during the execution of this project is the parameter values tuning which could be really cumbersome with so many prior. Next stage we are working on an adaptive algorithm that would take care of the parameter values through computational approach rather than manual calculation and tuning.

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