Deblurring Algorithm Using Alternating Low Rank Augmented Lagrangian with Iterative Priors

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Abstract. The paper focuses on the Enhanced Augmented Lagrangian method with sparse regularization for image deblurring. The method suggested by ALTERNATING LOW RANK AUGMENTED LAGRANGIAN WITH ITERATIVE A PRIOR is novel in the following ways. (i) Faster convergence leading to speeder execution through rank regulations (ii) using derivatives and low rank together as regularization priors (iii) penalty and regularization weights ensure that each iteration hits a global minimum with a steep descent. The proposed method begins with the lowest rank matrix, which is the sparsest matrix available. The final deblurred result is very successful in achieving good dB improvements through rank regulation.

Keywords: Augmented Lagrangian, Spare Regularization, Low-Rank Prior, Derivative Prior, Lagrangian multipliers, Block sparsity, image restoration.

1. Introduction
Photography is very common among people, and getting blurred photos out of clicked ones is very common nowadays. Zooming images and videos, deformation of lens, camera shake, hand, and object movement results in blur formation. Gaussian filter, average filter, and motion filter can introduce blur in images. [1] Gaussian blur is a type of image blurring added to each pixel and used to measure the transformation. Within a picture, a noticeable pattern of moving objects is motion blur. A motion blur produces a blur in a particular direction, such that the image appears to move. The motion blur is a filter that introduces a blur in a specific direction, such that the picture appears to shift. [2] Uniform blur occurs when the sharp picture is convolved with a spatially uniform blur kernel. In our research work, we mainly concentrate on image deblurring and image restoration. It is necessary to find the blurring degraded function H and sharp image x in restored algorithms. The degraded image can be interpreted in mathematical terms as y = Hx + n, where x is the real picture, n is the additive noise, [3], and H is the blurring operator. Optimization algorithms can obtain the solution for the ill-posed problem. The deblurring algorithm in the [15] proposed work proved (i) good results subjectively and visually (ii) better computation time (iii)out performs other algorithms.
2. Related Work

Research work is growing tremendously in the image deblurring area. Some of the deblurring algorithms that gained popularity earlier, like Discrete Fourier Transform, Wiener algorithm, Wavelet packet bases, Iterative Richardson-Lucy algorithm, Van Cittert[4], has been replaced today with prior-based deblurring algorithms. Some popular prior-based methods include L0, L1, Lp priors, Bayesian, Dictionary [10] Learning, Sparsity, Singular value decomposition, etc. Since traditional gradient-based priors failed, more sophisticated l0-norm-based prior, sparse prior coding, low prior rank [7], dark prior channel, etc., were implemented. The Alternating Direction Multiplier Method (ADMM) algorithm proposed in, together with the previous low rank, helps recover images of better quality and high dimensions. In solving constrained optimization issues in image processing, Augmented Lagrangian methods [5] have played an important role. The problem of blind deconvolution is modeled as a problem of L2 regularised optimization and solved using AL methods. Due to sparsity prior, gradient angle prior, and Lagrangian penalty parameters, the method provides improved stability, noise reduction, PSNR also SSIM values. The usage of adaptive sparse domain selection and adaptive regularization methods [6] in the proposed method provided better PSNR value and image perception. Deep learning methods, Coevolutionary Neural Network (CNN)[Error! Reference source not found.], Lagrange multiplier algorithm [[7]] helps to restore images, create super-resolution images, and reduces computation time. The proposed work can be compared with weighted l1-noise regularization model[[9]], Sparse representation using directional prior[13]. Least squared based deconvolution[14], Gradual reweighted regularization based on Alternating Direction Multiplier Methods[3], Augmented Lagrangian methods with BM3D frame prior[12], etc.

3. Proposed Methods

3.1. Simple Rank Iterative Minimization (SRIM) Algorithm

The Simple Rank Iterative Minimization (SRIM) algorithm is applied where the complexity of the data is not uniformly distributed, and the same complexity can be modeled with much smaller dimensions. The proposed SRIM algorithm removes the blur using additive low-rank modeling [8]. The low-rank approximation is obtained by a convex program named Principal Component Pursuit (PCP). The nuclear norm minimization lets us use low rank prior using Augmented Lagrangian Method (ALM). The ALM combines the ordinary Lagrangian method and penalty method without suffering from the disadvantages of these methods [11].

3.2. Block Augmented Lagrangian with Low-Rank Gradients Approach

![Block diagram of the proposed algorithm](image)

Figure 1: Block diagram of the proposed algorithm
4. Experimental Results
As shown in Figure 1 proposed algorithm is checked for accuracy and efficiency with various methods already in use. Extended researches show that our method outperforms inefficiency also effective when compared to other methods. The experimental comparison algorithms were divided into two categories: a) Prior based b) Intelligent based. Experiments were carried out on standard data sets. We present our experiment outcomes in 3 blur scenarios: Gaussian Blur, Uniform Blur, and Motion blur.

With various current prior-based deblurring approaches also deep learning-based deblurring methods, the planned algorithm is checked for performance and efficiency. Table 1 show that our method outperformed Deep learning-based deblurring algorithms in terms of PSNR and SSIM values.

Table 1: Comparison of the proposed approach on the same test images with Deep Learning approaches and blur kernels

| Metrics | Image Deblurring using CNN | Non-Uniform Deblurring | CNN for non-uniform motion blur[55] | Fully Conventional deep Neural network[56] | Deep Unrolling for blind deblurring | Proposed method |
|---------|----------------------------|------------------------|-------------------------------------|------------------------------------------|-----------------------------------|-----------------|
| PSNR    | 30.1                       | 17.36                  | 20.483                              | 21.947                                   | 27.3                             | **34.27**       |
| SSIM    | 0.9323                     | 0.391                  | 0.5272                              | 0.6309                                   | 0.88                             | **0.9836**      |

4.1. Motion Blur
The algorithm is tested for performing computation on the Berkeley dataset and Benchmark dataset. Table 2 reflects the proposed algorithm's comparison with numerous states of the art deblurring approaches-Buade’s non-local mean regularization technique, l1-denoiser, l2-denoiser p3-denoiser, Wl1-BM3D methods in terms of PSNR also SSIM values.

Table 2: Evaluation of the planned method with extra state-of-the-art deblurring techniques-the non-local mean regularization approach of Buade, l2-denoiser, l1-denoiser, p3-denoiser, Wl1-BM3D methods

| Motion blur | Deblurring performance of various methods for motion blur |
|-------------|----------------------------------------------------------|
| Image       | Buades P3-NLM l2-NLM l1-NLM Wl1-NLM P3-BM3D l1-BM3D Wl1-BM3D Proposed method |
| Lena PSNR   | 27.9 28.79 28.81 29.03 29.15 29.24 29.46 29.58 31.6726 |
| SSIM        | 0.749 0.808 0.809 0.835 0.846 0.852 0.873 0.884 0.9713 |
| Camera man  PSNR   | 27.24 28.02 28 28.26 28.38 28.42 28.61 28.72 29.2322 |
| SSIM        | 0.718 0.764 0.768 0.79 0.802 0.798 0.81 0.822 0.9503 |

4.2. Uniform Blur
The proposed research work is compared with Fast Iterative Shrinkage-Thresholding Algorithm(FISTA), L0-Sparse Deblurring ( L0-SPAR), Image Deblurring Block Matching 3D frames(IDD-BM3D), Adaptive Sparse Domain Selection- Adaptive regularization(ASDS-REG), Non- Locally Centralized Sparse Regularization(NCSR), Directional Prior Sparse Representation(DP-SR) and Non- Locally Centralized Sparse Regularization –Geometry driven Overlapping Cluster(NCSR-GOC) algorithms in this prior based deblurring category. Table 3 shows the PSNR, and SSIM evaluation outcome suggested with ordinary state-of-the-art approaches such asL0-SPAR, IDD-BM3D, and FISTA ASDS-REG, DP-SR, NCSR, BALLORG, and NCSR-GOC for many images presented in open-source dataset. The whole coding simulation is finished in MATLAB. It has been
seen that the proposed method performs well with uniform parameter values in almost every image.

Table 3: PSNR / SSIM Contrast among various FISTA, L0-SPAR, IDD-BM3D, ASDS- REG algorithms with the proposed 9*9scale uniform blur method

| Images      | Butterfly | Boats | Cameraman | House | Parrot | Lena | Barbar | Starfish | Pepper | Leaves |
|-------------|-----------|-------|-----------|-------|--------|------|--------|----------|--------|--------|
| UniformBlur | 28.37     | 29.04 | 26.82     | 31.99 | 29.11  | 28.33| 25.75  | 27.75    | 28.43  | 26.49  |
| FISTA       | 0.9119    | 0.8858| 0.8627    | 0.9017| 0.9002 | 0.8798| 0.8375 | 0.8775   | 0.8813 | 0.8958 |
| 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  |
| ASDE- REG   | 28.7      | 30.8  | 28.08     | 34.03 | 31.22  | 29.92| 27.86  | 29.72    | 29.48  | 28.59  |
| PROPOSED    | 29.7393   | 31.3671| 28.6026  | 34.451| 31.2818| 29.940| 28.254| 29.613 | 29.899 | 29.789 |
|             | 0.9656    | 0.9677| 0.9475    | 0.9807| 0.974  | 0.9592| 0.9366 | 0.9589   | 0.9539 | 0.9684 |

4.3. Gaussian Blur

As shown in Figure 2 Gaussian blur _PSNR vs. Iterations to It is evident from the graph that proposed deblurring reaches peak performance with a minimum number of iterations that show faster convergence. It is seen that a downward slope shows over fitting that takes place as quickly as after 35 iterations.

5. Conclusion
This paper proposes a novel Augmented Lagrangian method linking low rank and Iterative priors to Image deblurring. The proposed algorithm characterizes different combinations of spatially variant distortons, including Gaussian, Uniform, and Motion Blurs. Using penalty–function weights and Lagrangian multipliers, the unconstraned optimization problem is solved. The weights of regularization and penalty parameters also push the convergence to a clear global minimum in the
smallest possible number of iterations. The rank prior has a marginal effect on the algorithm's computational complexity, but a decrease in the number of iterations makes the algorithm a fast one. Our method by incorporating the mechanism of Augmented Lagrangian, Rank Prior, and Directional Gradient proved better in performance parameters when compared to similar existing learning-based and prior deblurring approaches. The reduction in the number of iterations justifies the execution speed and reduction in computation time. The proposed algorithm is innovative in many ways to avoid degradation in images and converges more rapidly, making it suitable for imaging and viewing devices in real-time. Future research will include testing the proposed algorithm in an embedded system and making the chipset platform incorporated into consumer technology.

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