

# Image Deblurring via Alternating Direction Method of Multipliers

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**Abstract:** The aim of *Multi-frame super resolution (MFSR)* is to estimate a high resolution image from a set of low resolution images. This task is highly ill-posed and computationally costly. A new MFSR forward model is proposed that reformulate the MFSR problem into a problem of multi-frame blind deblurring (MFDB) which is easier to be addressed than the other. MFDB problem can be sufficiently solved by attacking the resulting subproblems of alternating minimization using the alternating direction method of multipliers (ADMM). Experiments can be performed on synthetic and real images and can show the quality of the image and high speed in execution.

**Keywords:** ADMM, MFDB, Super Resolution, Blind Deconvolution

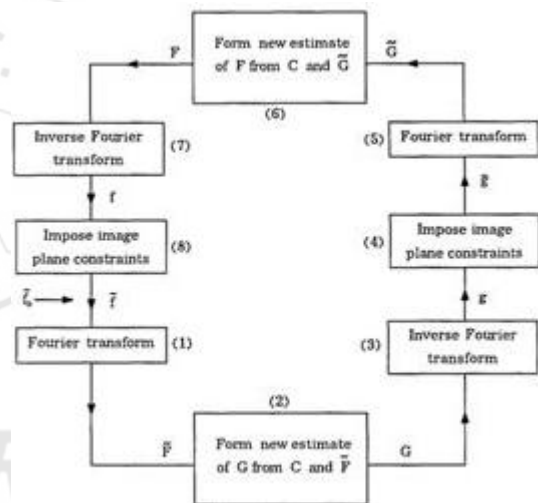
## 1. Introduction

Image Deblurring can be taking any image that is not sharply focused and processing it to make more clear to the viewer. In image processing restoration of a blurred image is the more publicized part. Several type of image distortions are there: noise incorrect focusing, white balance error, camera shake, exposure error, lens distortion, motion blur, gaussian blur, uniform blur, and more. People always like to capture their picture in sharp and focused, so only the viewers can see the picture correctly. Image Deblurring helps to view the picture correctly. Today the social Medias have a very good role in life which is mainly deals with a high collection of images. As we know a picture is made of many pixel values and whenever a change is occur in that pixel value then the blur can be occurred. The demand of high resolution image is increasing now a days. The below function outlines the equation of the image Deblurring,

$$g(x,y) = h(x,y) * f(x,y) + n(x,y) \quad (1)$$

Where  $f(x,y)$  represents the unblurred image,  $h(x,y)$  represents the blur kernel, and  $n(x,y)$  is the noise in CCD. Here the noise is not convolved with the blur kernel, because the noise originates from the random motion of electrons in camera's CCD array, which cannot be avoided and is not blurred. The blur kernel also called the point spread function which is caused by improper focusing or due to camera shake. There is now one point that has been smeared across multiple pixels. So for each pixel value we have to sum multiple pixels. So for each pixel we have to sum multiple pixel nearby vicinity is a simplest form of deconvolution. It always make a initial guess of blur kernel and blurred image and applies to deblurred image and a nes guess for the blur kernel. Then this can be converted into a iteration algorithm, where each iteration can make a new blur kernel that can be applied to blurred image for deblurring the image.

The diagram for a blind image deconvolution can be,



**Figure 1:** Flowchart of Blind Image Deconvolution

The main aim of this technique is to deblur a blurred image, so that the viewer can see the image correctly.

## 2. Literature Survey

### Deblurring Techniques:

- 1) Framelet Based Blind Motion Deblurring
- 2) Normalized Sparsity Measure
- 3) Fast Motion Deblurring

These are the three techniques in order to deblur a blurred image.

### 2.1 Framelet Based Blind Motion Deblurring

In digital imaging recovering a clear image from a single motion blurred image has long been a challenging problem. Here the main focus is on how to recover a motion-blurred image due to camera shake. In order to remove motion Deblurring from an image a regularization approach is used by regularizing the sparsity of both the original image and the motion-blur kernel under tight wavelet frame systems. Furthermore, the split Bregman method is used to solve the the resulting minimization problem efficiently [2]. The

experiments on both synthesized images and real images show that our algorithm can effectively remove complex motion blurring from natural images without requiring any details of the motion-blur kernel [2].

The simple equation used in framelet based blind image deblurring is

$$f = g * p + \eta \quad (2)$$

where \* is the discrete convolution operator, g is the original image to recover, f is the observed blurry image, p is the blur kernel, and  $\eta$  is the noise. State-of-the-art single image deblurring techniques are sensitive to image noise. Even a small amount of noise, which is inevitable in low-light conditions, can degrade the quality of blur kernel estimation dramatically knowledge about the blur. Blind deconvolution always allows the recovery of blurred image without knowing the blur kernel [4] recovering the original image from the blurry image is called deconvolution. Based on the availability of p, there are two categories of image deconvolution problems. If the blur kernel p is given as a prior, recovering the original image becomes a non-blind deconvolution problem [2].

This technique performs quite well in the case of motion-blurring being the uniform blurring, but this can not work in case of non-uniform motion-blurring, including image blurring caused by camera rotation and the partial image blurring caused by fast moving objects in the scene [2].

## 2.2. Normalized Sparsity Measure

Blind image deconvolution is used to deblur the image. many common forms of image prior used in this setting have a major drawback in that the minimum of the resulting cost function does not correspond to the true sharp solution [5]. many methods are used to get a better result. Here introduces an image regularization technique. The algorithm used in this technique is simple and fast. The mathematical representation can be;

$$g = ku + N \quad (3)$$

This convolution model can also be written as a matrix-vector product [7].

$$B = KL + N \quad (4)$$

where u and k are sharp image and blur matrix respectively. N is the sensor noise.

Image deconvolution can be further separated into two. First, the blur kernel is estimated from the input image. The estimation process is performed in a coarse-to-fine fashion in order to avoid local minima. Second, using the estimated kernel, apply a standard deconvolution algorithm to estimate the latent (unblurred) image [6].

Kernel estimation takes place only on high frequency of the image. Filters can be used to generate a high frequency

versions [5]. the filters can be  $\Delta x = [1, 1]$  and  $\Delta y = [1, 1]$ . the cost for spatially invariant blurring can be;

$$\min_{x, k} \lambda \|x \times y\|_2^2 + \frac{\|x1\|}{\|y1\|} + \varphi \|k\|_1 \quad (5)$$

This equation can have 3 terms. First can be the formation model of equation (1). second term is the regularizer that helps to scale invariant sparsity in reconstruction.  $\lambda$  and  $\varphi$  helps to control the strength of the kernel. This is a non convex problem and can be solve by optimizing the values of k and x.

Then the updation by these values can be done. That is given by;

$$\min_x \lambda \|x \times k - y\|_2^2 + \frac{\|x1\|}{\|y1\|} \quad (6)$$

This subproblem can be non convex due to the presence of regularization term [5]. the denominator can fix the sub problem then it becomes convex regularized problem. once the kernal is estimated then a variety of deconvolution method can be used to recover the original image.

## 2.3. Fast Motion Deblurring

Fast Motion Deblurring introduces a fast deblurring method that produces a deblurring result from a single image of moderate size [4]. Both latent image estimation and kernel estimation is get accelerated in an iterative deblurring process. A novel prediction step is introduced and it works with image derivatives rather than pixel values. In the prediction step [5], it uses a simple image processing techniques to predict strong edges from an estimated latent image, by using kernel estimation.

For this approach, a computationally efficient Gaussian prior is sufficient for deconvolution. That will help to estimate the latent image, as small deconvolution artifacts can be suppressed in the prediction. For kernel estimation, first formulates the optimization function using image derivatives, and accelerate the numerical process by reducing the number of Fourier transforms needed for a conjugate gradient method. Then shows that the formulation results in a smaller condition number of the numerical system than the use of pixel values, which gives faster convergence. Experimental results demonstrate that This method runs an order of magnitude faster while the Deblurring quality is comparable [4]. GPU implementation facilitates further speed-up, making the method fast enough for practical use.

A motion blur is generally modeled as

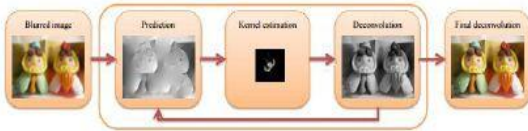
$$B = KL + N \quad (7)$$

where B is a blurred image, K is a motion blur kernel or a point spread function (PSF), L is a latent image, N is unknown noise, and \* is the convolution operator.

A successful approach for blind deconvolution is alternating optimization of L and K in an iterative process. In the latent image estimation and kernel estimation they can be,

$$L = \underset{L}{\operatorname{argmin}} \|B - K * L\| + \rho(L) \quad (8)$$

The Schematic diagram for fast motion Deblurring can be;

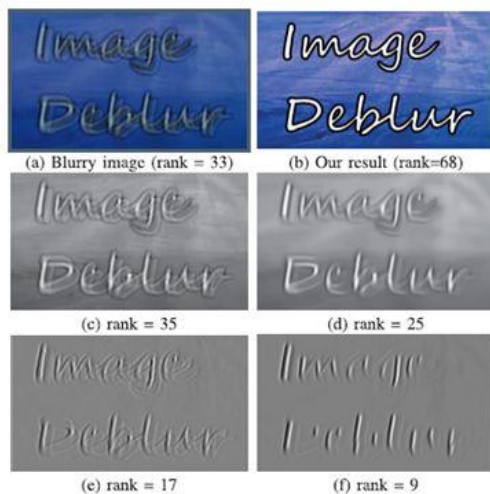


**Figure 2:** Fast Motion Deblurring

### 3. Existing System

#### 3.1 Low Rank Prior

This approach proposes a novel low rank prior for blind image deblurring [5]. That means information about the blur is not known. It is based on directly applying a simple low rank model to a blurry input image and thus reduces the blur effect by



**Figure 3:** Low Rank Prior Method

The algorithm used in image deblurring due to camera motion can be written as;

$$b = l * k + n \quad (9)$$

Where b represents blurry observation, l and n are latent image and noise respectively and k is the blur kernel.  $*$  stands for convolution operator. Convolutional blind deconvolution methods assume frequency- domains constraints on images [7].

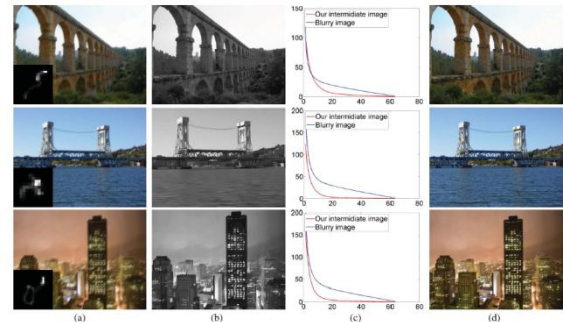
#### 3.1.1 A weighed nuclear norm minimization technique

A weighed nuclear norm minimization technique is used in order to find out the low rank approximation x from an observed matrix y [2].

$$\min_x \|y - x\|_F^2 + \|x\|_{w,*} \quad (10)$$

where  $\|x\|_{w,*}$  is the weighted nuclear norm defined by the sum of singular values and the corresponding non-negative weights [5].

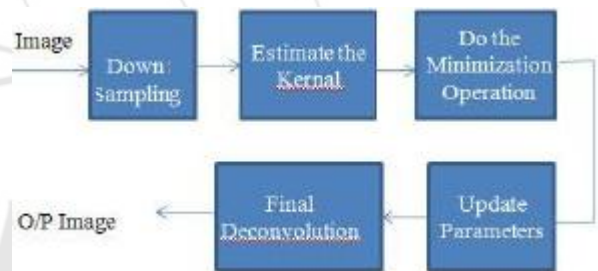
An observation included in this work is a LRMA model that can be used to deblur the image without knowing any information about the blur kernel.



**Figure 4:** Rank relationship between blurry and intermediate images



**Figure 5:** Main process in Low Rank Prior



**Figure 6:** Detailed version of low rank prior.

The main problems in Existing System are,

- 1) It fail if a blurred image contains rich textures, because most of textures will be removed and few sharp edges are retained for kernel estimation [5]
- 2) It fails in case of natural images.

### 4. Proposed System

The demand of high resolution image is increasing now a days. This technique can able to extract high resolution (HR) image or super resolution images from low resolution images ( LR) [7].super resolution is a process of combining a sequence of low resolution (LR)noisy blurred images to produce a higher resolution (HR)image or sequence. The general equation of deblurring introduced here,

$$\operatorname{Min} \|Ax - y\|_2^2 + T\phi(x) \quad (11)$$

First part of the equation for image deblurring and second part is called regularizer. ADMM can perform on images with unknown boundaries. Unknown boundary means that while deblurring the image can be divided to blocks. These

blocks can have fixed width. While deblurring all other methods create artifacts along these widths. ADMM avoids this problem. By adding a new weight factor in error minimizing term [7].

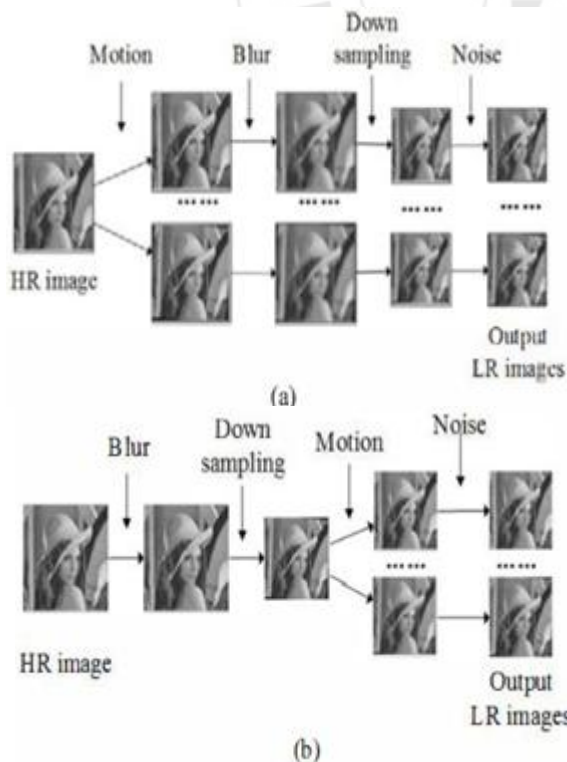
$$\text{Min } \|A^*w^*x-y\|_2^2 + T\phi(x) \quad (12)$$

This technique introduces a multi frame super resolution (MFSR) to estimate high resolution image from a low resolution images [8]. This MSFR problem can be reformulated into a problem of multi frame blind deblurring (MFDB). This technique adopt a matrix vector notation.

Multi-frame super resolution (MFSR) aims to estimate a high resolution image from a set of low resolution images. Such task is ill-posed and typically computationally costly. This proposes a new MFSR forward model, and reformulates the MFSR problem into a problem of multi-frame blind deblurring (MFDB) [11.] which is easier to be addressed than the former. Then further efficiently solve the MFBD problem via attacking the resulting subproblems of alternating minimization using the alternating direction method of multipliers (ADMM). Experiments on synthetic and real images show the effectiveness of the proposed method in terms of speed and image quality.

#### 4.1. Solving MFBD by the ADMM

The MFBD problem can be addressed by alternatively minimizing with respect to either  $u$  or  $h$  while keeping the other as a known constant. Each sub-problem could be solved by the ADMM. Figure shows the steps in solving MFBD



**Figure 7:** General forward model process; (b) proposed forward model

(i) Updating  $u$   
 For updating  $u$ , the sub-problem is to solve:

$$\min_u \frac{\gamma}{2l} \sum \|HU - G_k\|^2 + \phi(V_x, V_y) \quad (13)$$

Suppose  $V_x = \nabla_x u$ ,  $V_y = \nabla_y u$ , then the problem can be rewritten as:

$$\min_u \frac{\gamma}{2l} \sum \|HU - G_k\|^2 + \phi(\nabla_x u, \nabla_y u) \quad (14)$$

An algorithm is given for this technique

#### Algorithm 1

0. Initialization: set  $j, V_x^0, V_y^0, r_x^0, r_y^0 = 0$
1. Repeat
2.  $u^{j+1} := \text{argmin}_u (\frac{\gamma}{2l} \sum_{k=1}^l \|HU - g_k\|^2 + \frac{\alpha}{2} \|\nabla_x u - v_x^j - r_x^j\|^2 + \frac{\alpha}{2} \|\nabla_y u - v_y^j - r_y^j\|^2)$
3.  $v_x^{j+1} := \text{argmin}_{v_x} (\phi(v_x, v_y^j) + \frac{\alpha}{2} \|\nabla_x u^{j+1} - v_x - r_x^j\|^2)$
4.  $v_y^{j+1} := \text{argmin}_{v_y} (\phi(v_x^{j+1}, v_y) + \frac{\alpha}{2} \|\nabla_y u^{j+1} - v_y - r_y^j\|^2)$
5.  $r_x^{j+1} := r_x^j - (\nabla_x u^{j+1} - v_x^{j+1})$
6.  $r_y^{j+1} := r_y^j - (\nabla_y u^{j+1} - v_y^{j+1})$
7. until stopping criterion is satisfied
8. return  $u^j$

Lines 2, 3 and 4 of this algorithm are the main steps and they might pose computational challenges. In line 2, after differentiating and setting the derivative of the objective to zero, this can reach

#### Algorithm 1

0. Initialization: set  $j, V_h^j, r_h^j = 0$
1. Repeat
2.  $h^{j+1} := \text{argmin}_h (\frac{\gamma}{2l} \sum_{k=1}^l \|uh - g_k\|^2 + \frac{\beta}{2} \|h - v_h^j - r_h^j\|^2)$
3.  $v_h^{j+1} := \text{argmin}_{v_h} (l_{\nabla} (h^{j+1}) + \frac{\beta}{2} \|h^{j+1} - v_h - r_h^j\|^2)$
4.  $r_h^{j+1} := r_h^j - (h^{j+1} - v_h^{j+1})$
5.  $j = j + 1$
6. until stopping criterion is satisfied
7. return  $u^j$

In above algorithm, line 2 yields: where  $I$  is a unit matrix. It can also be efficiently computed by FFT algorithm.

Let  $t = h - r_h$ .

#### 4.2 Synthetic images

Four sequences of LR images have been generated. For the warping, rotations and translations were used. A  $3 \times 3$  uniform PSF has used for blurring. Finally, additive Gaussian noise with signal to noise ratio (SNR) levels between 10dB to 50dB has been added to the LR Images

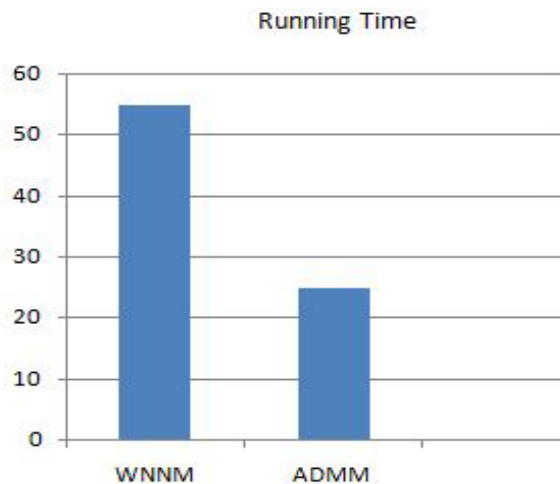
##### 4.2.1 Real images

Experiments can be also conducted on a real-world image sequence. In order to work with color image, this converted image from RGB color space to YCbCr color space, and

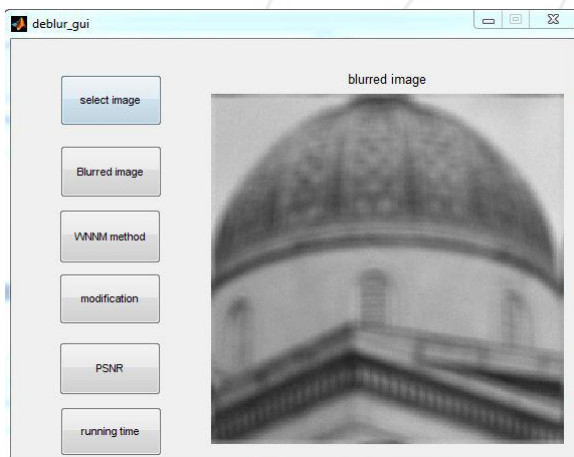
implemented the proposed method on luminance channel, and then converted the resulting image back to the RGB color space.

## 5. Result and Discussion

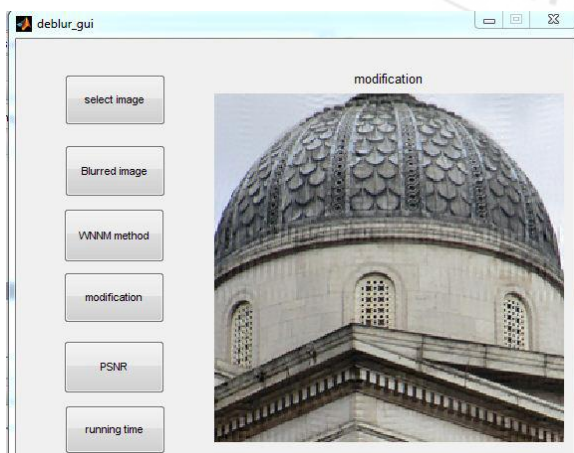
The Performance comparison graph between low rank prior and ADMM can be given as,



**Figure 8:** Performance Comparison



**Figure 9:** Blurred image



**Figure 10:** Output of ADMM

## 6. Conclusion

Image deblurring has a important role today. Three techniques were compared above among that ADMM shows a better performance. ADMM can be combined with low rank prior method and it can show better performance. ADMM also support for rich texture images.

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