

Survey on Various Image Deblurring Technique

Husna K¹, Harish Binu K P²

^{1,2}MEA Engineering College, State Highway 39, Nellikunn-Vengoor, Perinthalmanna, Malappuram

Abstract: In image processing image deblurring is important technique. The actual work in deblurring is enhancing the clarity of a picture. This paper surveys on various blind image deblurring techniques normalizes sparsity measure, low rank prior, Alternating direction method of multipliers For comparison various metrics are used. A low rank prior is method is usually used in order to deblur a blurred image. In this paper with low rank prior method an ADMM is used. The main aim of this paper is to estimate a high resolution image from a set of low resolution images. The task is computationally costly and is a highly ill posed problem

Keywords: ADMM, Low Rank Prior, Normalized Sparsity Measure, Blind Deblurring

1. Introduction

Today the use of social medias are in its peak. They are mainly deals with images. A camera can be used to record the faithful representation of scenes that we see but every image is more or less blurry. An image can be get blurred due to many reasons, that can be shaking of camera, presence of any obstacle in front of the camera etc. so the image deblurring is introduced to make the pictures to sharp and useful.

Images can be composed of picture elements called pixels. Each pixels can be assigned by intensity, used to characterize the color of small rectangular segments. A small image always contain around 65536 pixels while a high resolution image can contain 5 to 10 million pixels. Blurring can be arises in the recording of a digital image. that means some times the pixel may spill over the neighbouring pixels.

In image deblurring the main task is to recover the original, sharp image. Three technique is comparing here. In Normalized sparsity measure blind image deconvolution is used and it is a highly ill posed problem [1].

The blind and non-blind cases. In non-blind deconvolution, the motion blur kernel is assumed to be known or computed elsewhere; the only task remaining is to estimate the unblurred latent image [4].

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;

$$g = ku + N \quad (1)$$

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

$$B = KL + N \quad (2)$$

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;

$$\min_{x, k} \lambda \|x \times y\|_2^2 + \frac{\|x\|_1}{\|y\|_1} + \varphi \|k\|_1 \quad (3)$$

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. λ and φ 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;

$$\min_x \lambda \|x \times k - y\|_2^2 + \frac{\|x\|_1}{\|y\|_1} \quad (4)$$

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 kernel is estimated then a variety of deconvolution method can be used to recover the original image.

3. Low Rank Prior

This approach proposes a novel low rank prior for blind image deblurring [2]. 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 reduce the blur effect by protecting the edge information. This method for image deblurring is done by combining the low rank prior of similar patches from both blurry image and gradient map. a weighed nuclear norm minimization is also used to enhance the result of the deblurring technique.



Figure 1: Low rank prior favours clear intermediate results that help in kernel estimation.

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

$$b = l \times k + n \quad (5)$$

Where b represents blurry observation, l and n are latent image and noise respectively and k is the blur kernel. \times stands for convolution operator. Convolutional blind deconvolution methods assume frequency- domains constraints on images[3].

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

$$\min_x \|y-x\|_f^2 + \|x\|_{w,*} \quad (6)$$

where $\|x\|_{w,*}$ is the weighted nuclear norm defined by the sum of singular values and the corresponding non-negative weights [2].

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.

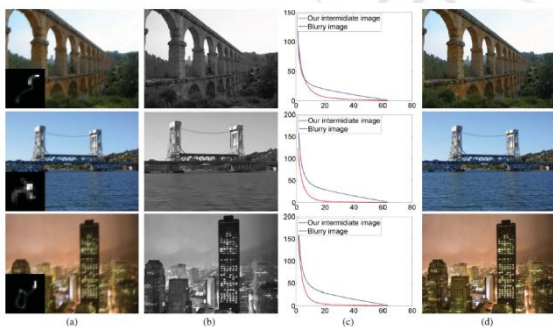


Figure 2. Rank relationship between blurry and intermediate images.

Since it is difficult to solve the model directly an efficient minimization algorithm is used here. This can calculate the blur kernel and can find out the latent image. this can be updated in each step and thus the final latent images will get. Sometimes the camera shaking can cause both rotation and translation. Then that can be modeled as;

$$b = \sum k_m H_m l + n \quad (7)$$

where b, l and n are vector forms of b, l and n . m is the camera pose and H_m is transformation matrix.

4. Alternating Direction Method Of Multipliers

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). 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 [9]. The general equation of deblurring introduced here is

$$\text{Min} \|Ax-y\|_2^2 + \tau \phi(x) \quad (8)$$

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.

$$\min \|A * w * y\|_2^2 + \tau \phi(x) \quad (9)$$

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 [10].

5. Discussion

Three algorithms are compared here. Among that better one has to find out. So their performance can be compared.

Table 1: Comparison Table

Algorithm	Advantage	Disadvantage
Normalized Sparsity Measure	Fast and cheap	Less Accuracy
Low Rank Prior	Deblurring can be enhanced by nuclear norm minimization	Kernel estimation can be affected by rich textures
ADMM	Remove all artifacts by adding weight	

6. Conclusion

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

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Author Profile



Husna K received her B.Tech. degree in computer science and engineering from the Jawaharlal College of Engineering and Technology, Kerala, in 2015. Right now she is pursuing her M. Tech degree in computer science at MEA Engineering College, Kerala from 2015 to 2017. Her research interests lie in Image Processing.



Harish Binu K P, Assistant Professor, MEA Engineering College, Perinthalmanna. Received the B.Tech degree in Computer Science & Engineering from NSS Engineering College, Palakkad, University of Calicut and M.tech degree in Computer Science from College of Engineering, Cochin university of Science and Technology. His research interests includes Image Processing and Digital design.