



Critical Analysis of Techniques used for Image Deblurring

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Abstract— *The quality of an image can significantly be degraded by the camera motion that causes the motion blur. The deblurring of motion blurred images is quite a hard problem since the direction of the camera motion can be arbitrary. Blurs found in the images can be uniform or non uniform that needs the estimation of point spread function(PSF). In this paper , various motion deblurring techniques has been widely surveyed and discussed. Throughout the analysis , we bring out some of the approaches for deblurring and further future work and directions.*

Keywords— *Spatially variant deblurring, Spatially variant deblurring ,Point spread function(PSF), motion blur, blind deconvolution*

I. INTRODUCTION

Image motion blur is a phenomenon that occurs when a photograph is taken in a low light conditions, a fast moving objects or from the relative motion between the object and camera. In recent literature , Image motion blur is generally modelled as the convolution between the sharp clear image and the blur kernel as shown in Equation(1),

$$g = k * f \quad (1)$$

where g is the observed blurry image , k being the blur kernel and f representing the latent sharp image that would have been captured if the camera remained still. $*$ indicates the convolution operation. If the blur kernel or Point spread function is known in prior the problem is said to be non blind deconvolution otherwise called blind deconvolution problem.

The problems of motion deblurring are underconstrained since there are certainly more unknowns than available measurements. These are typically blind deconvolution problem because the relative motion between the camera and the object becomes arbitrary.

As the topic is researched, a number of problems have been considered and broadly categorized into the uniform and non uniform blur,different depth layers etc. Multiple methods has been proposed to deal with such problem that basically focuses on estimating the blur kernel or point spread function(PSF) like weiner filter(for uniform blur), Recharadson lucy Algorithm (for non uniform blur), MAP Algorithm.

In section 2 the major work related to the uniform and non uniform blur is given followed by section 3 that includes the major description of the major algorithms like MAP Framewok and its modifications for spatially invariant blurs ,section 4 incorporates some models used to deblur the spatially variant blur are discussed . in the end Section 5 includes the conclusion and the scope of the further research.

II. RELATEDWORK

Most of the recent motion deblurring techniques are classified into: Single image motion deblurring and The multiple image motion deblurring. Also, based on the fundamental assumptions of estimating the blur kernel they can also be categorised as The Spatially variant PSF estimation and The spatially invariant PSF estimation.

To get rid of the problem of space invariant convolution that causes uniform blur the issues are studied extensively and much efforts has been taken. Early works include Recharadson-Lucy [24 , 25] that is an iterative approach to estimate the PSF while having little knowledge about noise. Later Fergus et al[1] integrated the variational bayesian approach of Miskin and Mackay[20] with blind deconvolution of single photograph by using the natural image statistics to estimate the blur kernel. Previously , Most of the methods worked by altering the traditional MAP framework iteratively for estimating the blur kernel and deducing the latent image[6],[13],[11],[21].the detailed analysis of the MAP framework given in[4].Jia[19] proposed a novel approach of restoring the motion blurred images using transparency, moreover their approach is able to restore both the motion blurred images and the object motion blurred images. Chunhe et al[23] presented a new deconvolution approach based on multi layer statistics prior that tries to adapt different statistic prior to the regions with different intensity and inhomogeneity while the yuan et al[22]proposed a multiscale approach to progressively recover blurred details. However all these above methods assume that the blur kernel is spatially invariant or uniform.



Fig 1: Deblurring result of shan et al[6]

However this is not necessary that the blur kernel is always spatially invariant it might be spatially variant or say non uniform across the image. When dealing with the spatially variant blur kernel all these methods are not able to produce fruitful or real world results for that there is a need for developing some more specialized approaches that will different pixel blur differently. The reason behind this non uniformity might be the movement of camera in rotational or translational motion while the shutter was open. Various models have also been proposed to deal with the projective motion of the camera Tai et al[15] modified the Reichardt-Lucy algorithm to incorporate the blur that arises when the camera undergoes ego motion. On the other hand Whyte et al[9] proposed a parameterized geometry approach and has shown that this approach can deal with a wider class of blur while a Fast Forward model was proposed by Hirsch et al[17] that takes into account the projective motion path blur model (PMPB) and fasten the work efficiently using Efficient Filter Flow (EFF) framework. Tai et al[16] also proposed a method of estimating the PSF efficiently using the coded exposure camera and the user interaction to recover the PSF.

III. SPATIALLY INVARIANT DEBLURRING

The foundation of the spatially invariant deblurring method is the underlying inference that the PSF or blur kernel of the observed blurred image is uniform throughout the image. Blind deconvolution is the most frequent way of recovering a sharp form of input blurred image when the kernel is unknown. This assumption of the unknown kernel helps largely in the solution of the deblurring process. A lot of research work has been done and numerous publications are there in signal and image processing. Earlier work can be found in the magazine of 1996[18]. Recently available algorithms have proposed various ways to solve the ill-posedness of the blind deconvolution methods by using natural image statistics for characterizing the latent image. In spite of the in depth research the results are far different than the reality, the recently available approaches are much in use.

In this section, we first look at the basic framework MAP algorithm, its failure and then will explore about the further modifications done in that to make it perform better. Finally we will discuss about their performance and results using the common set.

A. MAP Estimation and its Failure

The standard MAP algorithm has been widely researched and analysed by Levin et al in 2009[4] and Krishnan et al in 2011 [8]. The general assumptions of the blurred image is given in Equation (2),

$$y = k \otimes x + n \tag{2}$$

where, y is the observed blurred image, x is the latent sharp image that would have been captured if the camera was still during image capture and k is the blur kernel, n representing the noise (most common assumption for the noise is Gaussian noise). The goal of blind deconvolution is to infer both parameters x and k for given y in addition to that k is non negative and its support is very small compared to image size Here the simplest approach is Maximum-a-posteriori estimation seeking for a pair of (x, k) maximizing as in Equation(3),

$$p(x, k|y) \propto p(y|x, k)P(x)p(y) \tag{3}$$

For the simplicity of exposition, they assumed a uniform prior on k . The likelihood $p(y|x, k)$ is a data fitting term and $p(y|x, k) = -\lambda ||k \otimes x - y||^2$. The prior $p(x)$ favours natural images usually based on the observation that their gradient distribution is sparse. A common measure is Equation (4),

$$\log p(x) = - \sum_i |g_{x,i}(x)|^\alpha + |g_{y,i}(x)|^\alpha + C \tag{4}$$

Where $g_{x,i}(x)$ and $g_{y,i}(x)$ denotes the horizontal and vertical derivatives at pixel i and C is a constant normalization term. Exponent values < 1 lead to sparse prior and natural image usually corresponding to the α in the range of [0.5,0.8].

By using common measure from as an example the whole optimization problem is given by Equation (5),

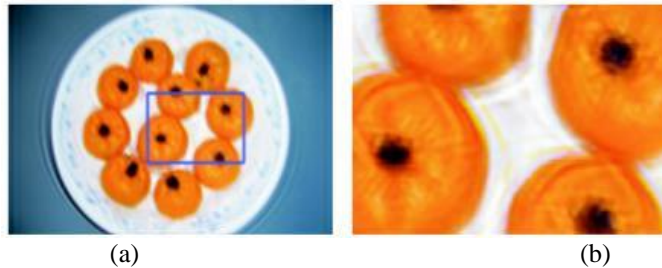


Fig 2: Image deconvolution result contains ringing artifacts around the edges (a) actual result of blind deconvolution (b) a magnified patch from (a)

ringing artifacts are clearly visible around the edges

$$(x, k) = \arg \min_{x, k} \lambda \|k \otimes x - y\|^2 + \sum_i |g_{x,i}(x)|^\alpha + |g_{y,i}(x)|^\alpha \quad (5)$$

It has been proved by Levin et al[4], the pair (x, k) optimizing the MAP(x,k) problem satisfies $|x| \rightarrow 0$ and $|k| \rightarrow \infty$, i.e. the most likely image under the priori Equation [5] is a flat image with no gradients. One attempt to fix the problem is to assume the mean intensity of the blurred and sharp images should be equal, and constrain the sum of k : $\sum_i k_i = 1$. This eliminates the zero solution, but it still favours the no-blur solution.

B. Modification and Extension of MAP

algorithm a) priors

After the introduction of basic MAP model by Fergus et al[1] in form of Equation[3]. Various modifications [6,8,11,26,9,12,28] has been proposed for MAP algorithm. A unified probabilistic model for both the blind and non blind deconvolution has been proposed by Shan et al[6] that solves the corresponding MAP problem by an advanced iterative optimization that alternates between blur kernel refinement and image restoration. To handle the randomness of noise they formed the likelihood prior like in Equation (6),

$$p(y|x, k) = \prod_{\partial^* \in \Theta} \prod_i N(\partial^* y_i | \partial^* y_i^c, \delta_{k_i}(\partial^*)) \quad (6)$$

Where $y_i \in I$ denotes the pixel value, y_i^c being the pixel value of in the reconvoled image. They used a set of partial derivatives operators represented by $\{\partial_x, \partial_y, \partial_{xx}, \partial_{xy}, \partial_{yy}\}$ the derivatives were computed with a maximum order of two since it has been shown with experiments two order derivative are sufficient to produce good results.

As for blur kernel prior they used the common exponentially distributed prior as in Equation (7),

$$p(k) = \prod_j e^{-\tau x_j} \quad (7)$$

As for the prior of latent image they approximated the distribution of natural image logarithmic gradient distribution and represented by two piece wise concatenated continuous functions in Equation (8),



Fig 3: Comparison of Spatially Invariant Deblurring results (a) Input blurred image (b) Cho et al[19] (2009) (c) Jia et al[14] (2010) (d) Krishnan et al[8] (2011)

$$\phi(x) = \begin{cases} -k|x| & x \leq l_t \\ -(ax^2 + b) & x > l_t \end{cases} \quad (8)$$

And introduced a global prior $p_g(x)$ and local prior $p_l(x)$ to both reduce the ill-posedness and ringing artifacts.

$$p(x) = p_g(x) p_l(x) \tag{9}$$

The deblurring results is shown in Fig 1.

Depending upon the analysis of Levin et al [4], one of the important property that make the blind deconvolution possible is the strong asymmetry among the dimensions of x and k . while the number of unknown in latent image x increases with the increase in image size on the other hand the dimensions of k remains small. However the large scale object can yield the stable kernel estimation since it is wider than kernel along with preserving the total variation of the latent signal along its edges. But still a blurred image with small objects in it having rich edge information along its edges can not produce accurate stable kernel estimate. The problem in estimating the correct kernel is due to the small structure.

So to deal with this Jia et al [5] proposed a new two way iterative approach to select the edges containing information for kernel estimation. The criterion measure the significance of gradient as in Equation (10),

$$r(x) = \frac{\|\sum_{i \in w_h(x)} \nabla y(x)\|}{\sum_{i \in w_h(x)} \|\nabla y(x)\| + 0.5} \tag{10}$$

Where, w_h is a $h \times h$ window centered at pixel x , 0.5 is to prevent producing a large r in flat regions. The deblurring results together with the results of [8,19,14] is shown in Figure 3 along with their comparison. In 2011 a novel prior approach was proposed by Krishnan et al[8] by using the ration of both the norms that is in favor of no- blur explanation . the optimization problem of novel prior is formed like in Equation (11),

$$(x, k) = \arg \min_{x, k} \lambda \|k \otimes x - y\|^2 + \frac{\|x\|_1}{\|x\|_2} + \phi \|k\| \tag{11}$$

The equation is subjected to the constraints that $k > 0$, and $\sum_i k_i = 1$ and then the problem is solved two phase iteratively. The L_1, L_2 norms function do have a number of drawbacks. Firstly it is non convex i.e unlike norms therefore there are multiple local minima. So finally it can not be expressed as a probabilistic prior. This is in direct contrast to norms that corresponds to the probabilistic model of the image gradient having hyper laplacian form and suitable only for non probabilistic framework .

It was observed by Fergus et al[1], Levin et al[4], and Krishnan et al[8] somewhere counter intuitively all the priors favors the blurry image to sharp image. That is there is a probable condition that the blurry image have lower cost than the sharp image. This is a direct results of chosen potential function decreasing towards zero, because blur attenuates at high frequency then the response of any derivative type filter will also be reduced and have low cost under the model.

Most of the recent work in the optimization problem used conjugate gradient approach for around 10 iterations. Some of them [1,7, 13] used multiscale approach that perform kernel estimation by varying image resolution in a coarse-to-fine manner to further improve the performance of small and large blur.

C. Evaluation and Comparison

In this section, we will mention the comparison of results of the spatially invariant deblurring algorithms that was mentioned in the literature of section A and section B.

Fig 3 shows that the deblurring results are quite encouraging despite of some of the ringing artifacts that arise around the edges of image but will be visible only when one clearly observes the image. Shan et al[6] used an iterative optimization between blur kernel estimation and image restoration nad provided a satisfactory result. While working on the same image Krishnan et al[8] produces a more clear result than previous one by using a novel prior.

In Fig 2 although all the researches used the two phase iterative approach and yielded some what similar results but they adopted different priors .but the results are still comparable in terms of speed. The speed of [13] is comparatively better than the other two and yield better result with a tolerate speed.

IV. SPATIALLY VARIANT DEBLURRING

On the other side of spatially invariant blur spatially variant blur assumes the non uniform blur which is found often in most of the real world problems. As discussed in section 3 most of the blind deconvolution problems works for estimating the single blurred kernel in the entire image. However in the real world problems where case arises of different motions, the blur cannot be modeled using single kernel and trying to deconvolve the entire image with single kernel will cause serious problems. Thus the focus here is to model the spatially variant methods that model the kernels for the non uniformly shaken images.

To begin with Levin et al[7] in 2006 proposed an approach that relies on the observation that the statistics of derivative filter are significantly changed by blur also assuming the blur results from constant velocity motion. They can limit the search to one dimensional box filter blur. They modeled the expected derivative distributions as a function of the width of the blur kernel by which they powerfully use to discriminate the regions with different blurs function of the width of the blur kernel by which they powerfully use to discriminate the regions with different blurs images in regions where there is no visual seam between the original and deconvolved images as in Equation (1),



Fig 4: Spatially variant deblurring results (a)input image (b) Gupta et al [2](2010) (c) Jia et al[19](2007)

They define the log-likelihood of the derivative in a window with respect to each of the blur model as in Equation (12) in order to measure how well the i -th window is explained by a k -tap blur in order to measure how well the i -th window is explained by a k -tap blur

$$l_k(i) = \sum_{j \in W_i} \log P_k(I_x(j)) \quad (12)$$

Where $I_x(j)$ is the horizontal derivative in pixel j after blurring and W_i is the window around pixel i . Then they smoothly segmented the regions for maximizing the log-likelihood of the derivative in each region. That will be defined by an energy function in Equation

$$E(x) = \sum_i -l(x(i), i) + \sum_{\langle i, j \rangle} e_{ij} |x(i) - x(j)| \quad (13)$$

Where e_{ij} is the smoothness term.

The smoothness term is the combination of two parts, First one is just a constant penalty for assigning the different levels to the neighboring pixels thus prefers smooth segmentation. The second part implies the fact that it is cheaper to cut the image in places where there is no visual seam between the original and the deconvolved images.

While O.Whyte et al[9] proposed a new parameterised geometric model for dealing with the non uniform blur of images. They model the blurring process in term of rotational velocity of the camera during exposure to the object. They applied there model to two different algorithms in which first uses a single blurred image and the second one uses both a blurred image along with a sharp but noisy image of the same scene. But the drawback of the problem lies in itself since the availability of the copy of same image is a rare incident.

Meanwhile, Michael Hirsch et al[3] in 2011 developed a fast forward model based on the efficient filter flow(EFF) framework incorporating the particularities of the camera shake. This paper basically combines the structural constraints of the PMPB model and the EFF framework to make the blind deconvolution computationally efficient. EFF approximates The non stationary blur as the sum of R differently blurred patches as in Equation (14),

$$g = \sum_{r=1}^R a^r * (w^r \odot f) \quad (14)$$

Where g be the blurry photograph for which we would like to recover a sharp version f and w^r denotes the weighing image. While a^r denotes the non stationary blur. Here patch can be written as $(w^r \odot f)$ and \odot signifies the pixel wise product. Since $w(r) \geq 0$ is chosen to be only non-zero in a small region of f , the convolution of each patch can be implemented efficiently with short fast Fourier transforms (FFTs). If the patches are chosen with sufficient overlap and the $a(r)$ are distinct, the blur expressed by the EFF will be different at each image location, varying gradually from pixel to pixel. Furthermore Gupta et al[2] in 2010 introduced the Motion Density Function(MDF) that records the fraction of time spent with each discrete portion of space of all possible poses of camera to elaborate the spatially varying blur kernel. They decomposed the blur kernel into different kernels as i Equation (15),

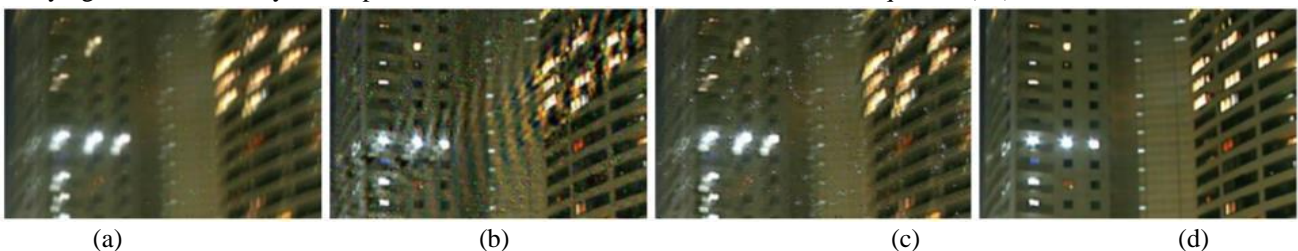


Fig 5: Comparison of Spatially variant Deblurring results (a) Input blurred image (b) Levin et al[4] (2007) (c) Jia et al[14] (2012) (d) Cho et al[19] (2011)

speed. but it fails when dealing with moving or deformable objects.

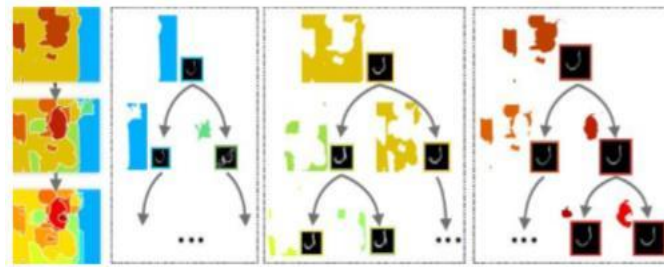


Fig 6: Region Tree Segmentation [6]

Thus similar to blind deconvolution with the sparse prior

$\phi(\cdot)$ as well they form energy maximization that is given in Equation(16),

$$E(x, k) = ||(\sum_j (\alpha_j k_j) * x - y|)^2 + ||\phi(|\partial x|) + \phi(|\partial y|) + \lambda_1 ||A||^{\gamma} + \lambda_2 ||\nabla z$$

$$k = \sum_j \alpha_j k_j \quad (15)$$

Where, A is the MDF matrix where each element α_i denotes the density at each pose j. The deblurring results are shown in Fig (5) although MDF can solve some non uniform blurring problem but is still outperformed by depth aware deblurring.

Now for the most recent work, jia et al[5] in 2012 analyzed that existing non uniform deblurring approaches can not handle images with different depth layer. Because in case where the object is not too far from camera the spatially varying Point spread functions (PSFs) arise along with the abrupt changes about the boundaries and making the near by things more blurred than the distant one. When the objects are a different depth layer the smooth kernel change is no longer applicable on the its edges. So they applied the two images to use two view stereo analysis to form a depth aware blur kernel that handles this situation. Two-view analysis is based on Equation (17),

$$I_m(x) = I_r(x + \frac{f}{z(x)} \delta b)$$

$$= I_r(x + d_m(x)) \quad (17)$$

Where, I_m is the unblurred matching image and I_r is the reference image. δb is the baseline distance between the two camera projection centre, $z(x)$ denotes the depth of x in the matching view, $d_m(x)$ is the disparity of the point that projects to x in I_m . According to the Equation (17) they model different depth layer to different blur sub kernel and introduce a region tree segmentation method for separating depth layer as in Fig (6).

V. CONCLUSIONS

After going through numerous methods in the survey it was found that most of the recent deblurring techniques incorporate the spatially invariant single image and multi image deblurring, and the spatially variant single image and multi image deblurring.

Spatially invariant methods often include the application of MAP algorithm but the shortcoming of standard framework of MAP is pointed out many times in estimation theory and statistical signal processing since in $MAP_{x,k}$ problem we can never collect enough measurements because the number of unknown grows with image size. Although later various researchers have modified the MAP algorithm in order to improve the estimation. On the other hand for dealing with non uniform blur a number of different spatially variant deblurring methods have been developed. Some of them include the separation of depth layer of objects and used two view stereo analysis for estimating the depth aware blur kernel. Meanwhile a Fast forward model was developed that was found to be efficient and a parameterized geometrical approach was also used for dealing with non uniform blur that caused due to rotatory motion of camera during image capture. After evaluating and comparing results of the recently available approaches it was observed that Shan et al[6] successfully deblurred most of the motion blurred images but fails when the blurred image is not shift invariant however Jia et al[19] requires the accurate alpha kernel estimation for success. This methods proves to be optimized than other methods to compute blur filter for 1-D and 2-D motion. However approach by Chunhe et al[23] is visibly more better than previous approach. In case of spatially variant deblurring the results produced from model of O.Whyte et al[9] seems to be appreciable but requires the availability of two images of the same seen that is a rare incident. Meanwhile Hirch et al[17] development proves to be more efficient than other available approaches in terms of performance and

During the survey it was observed that there still exist a scope of enhancing the performance and handling the more sophisticated problems like sharp changes in PSF. However to achieve better performance and in less time with little information is still possible and should be encouraged to research.

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