Denoising and Deblurring by Gauss Markov Random Field: An Alternating Minimization Convex Prior

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Abstract: ***In this work we propose the problem of denoising and deblurring of a degraded noisy blurred image in a single frame work. Firstly, we denoise the image containing Additive White Gaussian Noise (AWGN) and implement a non-blind deconvolution method to deblur the image using Gauss Markov random field (GMRF) prior. We estimate both the all-in-focus image and the blur sigma corresponding to the space-invariant point spread function (PSF). This problem is highly ill posed to obtain an initial estimate of blur map. We implement an MAP-GMRF alternating minimization framework to obtain the blur kernel. We calculate analytically the gradients on two direction with respect to the unknowns and show that the proposed objective function can successfully optimized with the steepest descent technique. We show results using the Gauss-Markov random field [2] prior. We show that fine details and structure information's are preserved by the GMRF regularizer. We compare the results of our algorithm with state-of-the art techniques and provide both qualitative and quantitative evaluation.***

Keywords: Gauss Markov random field, Non-blind deblurring, Additive White Gaussian Noise, Point Spread Function

1. Introduction

Non-blind deconvolution is active research area in the fields of computer vision and image processing from past several decades. However, most available existing deblurring methods directly applying deconvolution on the degraded image and are very much sensitive to noise. Most method address only deblurring of a image assuming zero noise. To enhance the performance of non-blind deconvolution of noisy image, we propose a novel framework method. In the proposed framework, firstly designed to denoise image using non-local filter. Then, non-blind deblurring techniques are employed to deblur space-invariantly blurred images respectively. The proposed framework is more generic MAP-GMRF and can be easily extended to existing denoising techniques. The conducted experiments have validated the effectiveness of the proposed framework, and have demonstrated that the proposed method outperforms other state-of-the-art methods in both preserving image structures and suppressing noise.

Deconvolution algorithms proposed by Latha et al. [4] and many authors mainly focus on space in-variant PSFs which are projections of blur descriptor caused by camera shake duing image acquisition. Bayesian variational inference framework is the estimation of image is based on Gaussian noise [6] and image gradient, prior is learnt by mixture of Gaussian. MAP based method with different image prior and likelihood functions derived from image statics are developed by are efficient and faster. Edge based selection models proposed by some researchers for sharpness measurements and blur kernel estimation. To reduce the running time of the algorithm [7] proposed a novel method by applying a gradient based edge prediction model. The proposed model in this work uses MAP-GMRF [5] frame work. This algorithm is efficiently optimized to predict latent picture edge by iterative process under some constrains. The complexity of this method is less, some times results are affected by noise[6] hence a novel denoising is first done before the deblurring iterations..

2. Literature Survey and Related Work

Deblocking Filters are proposed by Vasantha et al. [10] to remove the artifacts of the restored image. Cho et al. [1] proposed a robust method that explicitly model the degradation process. However, this method is only effective when outliers are sparse in well-localized areas. Krishnan et al [3] proposed a Fast image deconvolution using hyper laplacian priors. Latha et al.[4], [14] proposed a method to deblur space-variant defoused image using alternating minimization techniques.

Latha et al. [4] proposed a deconvolution framework, inspired on depth estimation reconstruction. This algorithm is computationally complex and time taking. Li et al.[5] employs a random noise model which reduces ringing artifacts due to mismatch of sigma estimation. This method is time consuming and some time not efficient for suppression of noise. The method demonstrated by Latha et al. [20] estimates the blur-map initially to deblur the image using saliency models in compressed domain techniques. [4], that works with different image priors. The method can handle saturation [16] by discarding saturated pixels and uses a prior non-linear space. The method is later extended to deconvolution [19], where a two step reconstruction that improved the saturation handling is introduced [17]. The first step reconstructs the latent image by discarding unreliable blurred pixels, and the second one works on the regions that were masked out in the first phase. Our method is simpler and does not need to distinguish reliable from unreliable pixels. Sadhan et al. [21] proposed a Image understanding models for Semantic Segmentation of Graphics and Text using Faster-RCNN, is used for prepossessing the degraded data. Whyte et al. [3] claim that while saturation can be handled by discarding saturated pixels, a better solution is obtained by modifying the data term to handle saturation explicitly. The saturation operator (clipping) is approximated with a smooth function allowing to compute its derivative. In this work, we present a similar approach, but it does not require to approximate the non-smooth saturation operator. Vasantha M V et al[10] presents a two-phase algorithm for recovering depth using Context Based Adaptive Variable Length Coding [21] and deblocking Filter of H. 264 standard. We use gradient descent with Gaussian Markov random field [5] prior algorithm to estimate blur kernel and latent image, thus preserving fine details and solving the optimization problem.

3. Proposed Method and Problem Definition

The method proposed in this paper uses an alternating minimization frame work to estimate the blur kernel and the latent image, given a single noisy-blurred image. Initially we model the blur map and the focused image as two dependent GMRFs and optimize a suitable energy function using the graduated convexity algorithm. Subsequently, We show the superiority of the GMRF regularizer for preserving fine details and structure in the restored image. Fig. 1 shows the focused, blurred & noisy and reconstructed image respectively. Space-invariantly blurred image and its ground image is shown Fig. 2.

Figure 1: a) Focused Image b) Blurred & noisy image

Figure 2: Space-invariantly blurred image and Ground truth image text [9]

a) Image Formation

The point spread function (PSF), is the response of a camera to a point light source. As shown in Fig. 2, a point light source at a distance D from the lens will be imaged as a circular disc on the image plane with radius rb given by

$$r_b = Rv\left(\frac{1}{f} - \frac{1}{v} - \frac{1}{D}\right) \quad (1)$$

where R is the radius of aperture of the lens. Considering lens aberrations and diffraction, the PSF is approximated by a 2D circularly symmetric Gaussian function [11]. The standard deviation of such a PSF is given by

$$\sigma = \rho r_b = \rho R v\left(\frac{1}{f} - \frac{1}{v} - \frac{1}{D}\right) \quad (2)$$

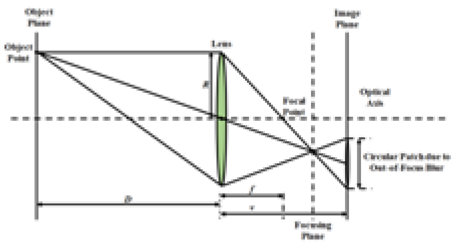

Figure 2: Image degradation model [8]

b) Degradation models

The formation of a space variantly blurred images can be modeled as

$$y = H(\sigma) * x + \eta \quad (3)$$

The matrix H represents the operation of space-variant blurring on the focused image x. The additive noise η is assumed to be zero mean Gaussian distribution. The PSF is given by

$$h_p(i,j;k,l) = \frac{1}{Z(i,j)} exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma^2(i,j)}\right) \quad (4)$$

where

$$Z(i,j) = \sum_k \sum_l exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma^2(i,j)}\right) \quad \mathbf{(5)}$$

C) Mathematical modeling by GMRF prior

Initially, we propose to model the blur map σ and the focused image x as two independent GMRFs and obtain their maximum a-posteriori (MAP)estimates. Using Bayes' rule and upon taking logarithms

$$Z(i,j) = \sum_k \sum_l exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma^2(i,j)}\right)$$

$$(\hat{\sigma}, \hat{\mathbf{x}}) = \arg\min_{\sigma, \mathbf{x}} \{\log[\mathbf{P}(\mathbf{y}|\sigma, \mathbf{x})] + \log[\mathbf{P}(\sigma)] + \log[\mathbf{P}(\mathbf{x})]\} \quad (6)$$

P(σ) is the probability density function(pdf) of the sigma map and P(x) is the prior pdf of the focused image x.

$$(\hat{\sigma}, \hat{\mathbf{x}}) = \frac{1}{2}\|\mathbf{y} - \mathbf{X}.\mathbf{h_p}\|_2^2 + \lambda_\sigma \sum_{c\in C} \mathbf{V}_c(\sigma) + \lambda_x \sum_{c\in C} \mathbf{V}_c(\mathbf{x}) \quad (7)$$

The MAP estimate can be equivalently written as

$$(\hat{\sigma}, \hat{\mathbf{x}}) = \frac{1}{2}\|\mathbf{y} - \mathbf{X}.\mathbf{h_p}\|_2^2 + \lambda_\sigma \sum_{c\in C} \mathbf{V}_c(\sigma) + \lambda_x \sum_{c\in C} \mathbf{V}_c(\mathbf{x}) \quad (8)$$

where c is a clique, C is the set of all cliques and $V_c(\cdot)$is the potential associated with clique c. The gradient update steps to estimate both σ and x alternatively, are given as

$$\sigma = \sigma^{old} - \alpha_\sigma\left(\frac{\partial e_p}{\partial \sigma} + \frac{\partial}{\partial \sigma}\left(\lambda_\sigma \sum_{c\in C} \mathbf{V}_c(\sigma^{old}) + \lambda_x \sum_{c\in C} \mathbf{V}_c(\mathbf{x})\right)\right) \quad \mathbf{(9)}$$

$$\mathbf{x} = \mathbf{x}^{old} - \alpha_x\left(\frac{\partial e_p}{\partial x} + \frac{\partial}{\partial x}\left(\lambda_x \sum_{c\in C} \mathbf{V}_c(\mathbf{x}^{old}) + \lambda_\sigma \sum_{c\in C} \mathbf{V}_c(\sigma)\right)\right) \quad \mathbf{(10)}$$

where α_σ and α_x are gradient step size parameters for estimation of σ and x respectively. ep is the data term. Assuming x as a GMRF

$$\frac{\partial}{\partial x}(\mathbf{V}_c(\mathbf{x})) = 2 * [(\mathbf{x(i,j)} - \mathbf{x(i,j-1)}) + (\mathbf{x(i,j)} - \mathbf{x(i,j+1)}) + (\mathbf{x(i,j)} - \mathbf{x(i-1,j)}) + (\mathbf{x(i,j)} - \mathbf{x(i+1,j)})] \quad \mathbf{(11)}$$

Using the degradation model in Equations the gradient of the error term e p with respect to x is

$$\frac{\partial \mathbf{e_p}}{\partial \mathbf{x}} = \mathbf{H}^T(\mathbf{Hx} - \mathbf{y}) \qquad (12)$$

Using the degradation model in Equation the gradient of the error term e_p with respect to σ is

$$\frac{\partial \mathbf{e_p}}{\partial \sigma} = \mathbf{X}^T(\mathbf{Xh_p} - \mathbf{y}) \qquad (13)$$

The MAP-GMRF technique used to estimate σ and x in an alternating fashion is given in algorithm 1.

Algorithm 1:

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Input : Partially blurred observation y, using [1]
α = Learning rate or the step size, λ = Regularization parameter
i ← 1 ; iterX ← 1 ; iterS ← 1
x_out = 1000; x_in = 1; x_iter = 50; σ_iter = 50
while (x_in ≤ x_out) do
    while (iterX ≤ x_iter) do
        solve for ∂E/∂x using Eq. (23)
        x_new = x_old − α ∂E/∂x
        x_old = x_new
    end while
    while (iterS ≤ σ_iter) do
        solve for ∂E/∂σ using Eq. (24)
        σ_new = σ_old − α ∂E/∂σ
        σ_old = σ_new
    end while
end while
```

4. Experiments and Results

First, we study the of the different models individually. Our results are compared to four state-of-the-art methods. We compared our results with the methods of Li et al. [12], Krishan et al [13], Pan et al [7] and Cho et al. [3]. The first one uses the kernal estimation of motin blur. The second one is based on the Richardson-Lucy deconvolution algorithm [13], which is more robust to ringing, and in this version, also handles boundary conditions. Then, we present qualitative and quantitative results on both synthetic and realistic data set. And show that our model of the complete degradation pipeline improves the results. This experiments on synthetic and real images are conducted using a 2.2 GHz i5 processor with 8GB RAM.

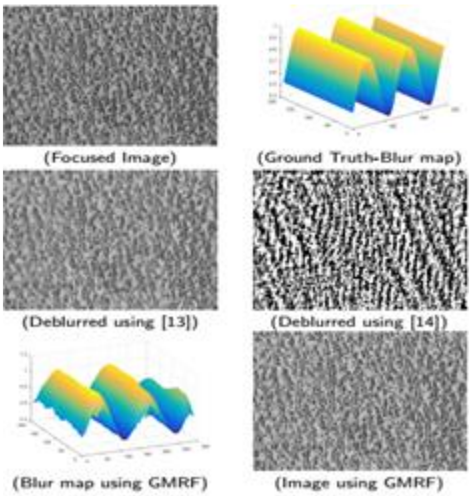

Figure 3: a) shows the results obtained on synthetic calf image with sinusoidal shaped blur map with blur parameter σ varying from 0.4 to 1.5. The image restored using other state-of-the method is shown in Fig 3 c) and d). The ground truth blur-map and the estimated blur-map is shown in the Fig. 3 b) and e) respectively. The result of latent image estimated using the proposed MAP-GMRF algoritham is shown in Fig. 3 f).

Fig. 3 a) Results obtained using state-of-the and our proposed method.

Another set of results obtained on synthetic face data is shown in fig. 4. Space-invariant blur is added to a noisy image.

Figure 4: a) clear image b) Noisy image c) Blurred image d) Reconstructed image

The performance measurement of the proposed alternating minimization technique for image restoration is calculated by PSNR and SSIM measurement. The PSNR and SSIM obtained by using GMRF priors and other state-of-the art is given in the below Fig. 5 and Fig 6 respectively.

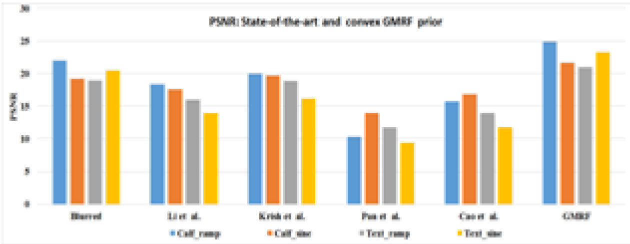

Figure 5: PSNR values of text and face images

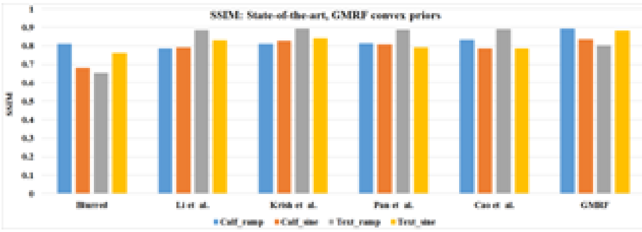

Figure 6: SSIM values of text and face images

We compared our results with the methods of Li et al. [16], Krishan et al [3], Pan et al [7] and Cho et al. [1]. Table 1 and 2 shows the PSNR and SSIM measurement of the proposed method.

Table 1: PSNR values

Image	Blur Type	Blurred	GMRF
CALF	Ramp	22.0453	24.8412
CALF	Sine	19.2142	21.7017
TEXT	Ramp	18.9222	21.0314
TEXT	Sine	20.5021	23.2980

Table 2: SSIM values

Image	Blur Type	Blurred	GMRF
CALF	Ramp	0.8103	0.8940
CALF	Sine	0.6811	0.8371
TEXT	Ramp	0.6533	0.8039
TEXT	Sine	0.7587	0.8830

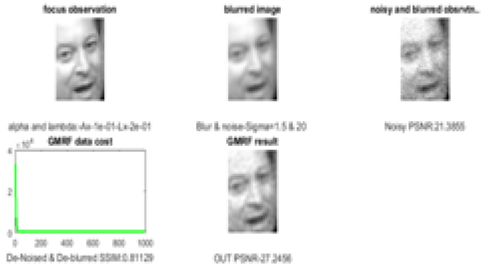

Figure 7: a) clear image b) Blurred image c) Noisy-blurred image d) GMRF data cost e) Reconstructed image

5. Conclusion

This works implements both deblurring and denosing in a single frame work by MAP-MRF Optimization using GMRF prior. We denoise the image containing Additive White Gaussian Noise (AWGN) and performed deconvolution to deblur the image using Gauss Markov random field (GMRF) prior. We estimated both the all-in-focus image and the blur sigma corresponding to the blurred image. We implemented an MAP-GMRF alternating minimization framework to obtain the blur kernel. The results shows that fine details and structure information's are preserved by the GMRF regularizer. We have compared the results of our algorithm with state-of-the art techniques.

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