Blind Motion Deblurring Using Non-edge Specific Adaptive Scheme

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Abstract : Deconvolution of a true image from a degraded image from unkown blur kernel is blind image deconvolution. In real life application, assuming a known kernel for deblurring is not a suitable solution. Existing methods are not robust , in this case an algorithmic approach to combined blur identification and image rebuilding is essential. This paper mainly focus on effective method of blind motion deblurring toward image diversity. This method is a combination of two schemes, edge specific and nonedge specific scheme.Such a combination is a new approach in every aspect. A prediction and detection method comes under edge specific scheme. It is sensitive to diversity of edges of present in natural pictures. Different images have different statistical composition, non-edge specific scheme is sensitive to these statistical variations. A novel non-edgespecific adaptive scheme (NEAS) is proposed,which work well on diversity of natural images. NEAS can highlight the features from both edge specific and non-edge specific schemes. The performance of NEAS is compared against state-of-art using a very large image set.

***IndexTerms* - blind motion deblurring; kernel; deconvolution; image restoration.**

I. INTRODUCTION

Blur is the degradation of image quality. Mathematically it is the convolution of blur kernel over a sharp image. There should be some mechanism to restore the quality of image. This process of blur removal and restoring the sharp image is deblurring. Blur can be of different types object motion blur, out-of-focus, camera motion blur. Image quality can be reproduced by removing blur in the image. Even without the usage of complicated techniques image quality can be improved using blind deconvolution. In real life application, assuming a known kernel for deblurring is not a suitable solution. In such a situation an approach which can join blur detection and image restoration is essential. Practical solution for this is to apply blur deconvolution.

If one can effectively detect the edges, then half job is done. This is the basis of different edge specific methods. They highly depends on Large Scale Step Edges (LSED). By the efficient prediction and detection LSED, edge specific method performs well. Different filters are used by prediction based method to make this job easier , they can restore simple textured images but fails when come to highly textured images. Detection based method will make use of the sharp version of blurred image, they fails to provide robust kernel estimation.

On the other hand, non-edge specific scheme uses image measurement which favours sharp expansion of image. This fails to work well on large database of images, but work well for small number of natural images. Marginalization method of non-edge specific scheme is which works as iterative approach which alternate between prior kernel and sharp image until it reaches a margin of acceptance. Highly textured images which cannot be tracked by the edge specific scheme can be identified by using non-edge approach.

Natural images are not the same always. They have statistical variations. Non-edge specific approach suffers from such differences in natural images. This make them fail towards image diversity. Edge specific scheme as its name implies its accuracy depends on ability to detect edges if it fails the performance will be limited.

A novel non-edge specific adaptive scheme (NEAS) for blind motion deblurring is proposed inorder to overcome these difficulties. It combines the one of the two methods from each scheme.i.e. LSED prediction and marginalization using prior distribution. The prediction method of edge specific scheme provides robustness among different variation of natural images, whereas non-edge specific scheme can provide robustness by providing efficient initial priors and regularization term.

II. RELATED WORKS.

Blurring of a image can cause some information of true image is lost. Fluctuations and variations image capturing process make blurring inevitable in many realistic situations. Blurring components and other noise influences make the recovery process difficult. So it is said to be recovery of the sharp image is more challenging, the general method of motion deblurring is blind deconvolution[12]. Blind deblurring process is an ill-posed problem as the known data is lesser than the unkown. In this, not only the blurring operator is ill-posed, but the problem also is, because it has infinite number of solutions that can match the degraded image. The deblurring efficiency can be enhanced by understanding the deblurring elements and noise factors involved in it.

Variational Bayesian methods have recently been applied to image deblurring. A Bayesian approach to estimate the blur kernel is proposed by Fergus et al.[1]. This is done by use of the marginal probability. Uncertainty is imposed on either unclear sharp image or unclear blur kernel, or both using Bayesian inference framework. In order to control the ill-poseness in blind deconvolution algorithms, Bayesian framework is applied to condense the size of the search space, where the solution lies. In image deconvoluton methods conventionally the blur kernel is imagined to be spatially invariant. Practically this invariance is breaked under the influence of composite motion or certain other factors. Because of this spatially variant blur is said to more applicable in practical scenarios. But deblurring spatially variant blur is more difficult than the invariant. A technique to deblurr this type of blur[2][11] is proposed which make use of prior knowledge. A proper estimation rule is needed for this, so it uses Gaussian blur. On analysing MAPx,k approach it leans towards no-blur explanation. The variational Bayes approach performs better from all existing methods. They follow a coarse to fine approach which can optimizes noise influence, such that frequencies lesser than the noise variance approximated to zero.

Levin et al.[2][11] proposed an improved efficient marginal likelihood approximation. MAP problem is studied and analysed deeply in it. Levin et al.'s method differs from [1] in that the target distribution to be approximated is p(x|y;h) rather than p(x; h|y).Krishnan et al.[4] analyze all the present priors and introduce an novel sharp-favor prior for deconvolution. Blurring process can cause loss of information, this make it severely ill posed. So recovering a PSF from this is challenging. A method is proposed [5] for efficient estimation of PSF. An algorithm is proposed which can measure blur by estimating PSF by the application of sub pixel edge location. It predicts PSF by using the sharp version of blurry input.

Jinshan Pan and Zhixun Su[6] proposed a method to regularize a blur kernel estimate. Each Alternating Direction Methods (ADMs) internal problems have solutions with their closed forms. An adaptive structure map is adopted, therefore the delta kernel is simpler and no salient edge selection is required. In this instead of recovering latent images, it performs kernel estimation on high frequencies of images. Selection of salient edges from interim recovered images in every iterations is needed in this approach.Thus,kernel estimation process is simpler. This method is very efficient, because each sub-problem that is designed by proposed algorithm has its own explicit solutions and also this requires much less computational time.

Most of the existing methods have been tested only on very small sets of natural images. In fact, several algorithms are able to produce satisfactory results only on a small number of chosen images. For real life application the relevance of applying different deblurring methods are hindered due to its poor robustness, particularly in case of highly varied natural images. The NEAS is an elegant combination of the marginalization method and the LSED prediction method. It alternates between a non-edge specific to an edge specific scheme, which can give a robust algorithm.

III. PROPOSED SYSTEM

NEAS is a combination non-edge specific scheme and edge specific scheme. If following a non-edge specific scheme alone for deblurring, it only for few number of natural images, hard for thousands of natural images and marginalization work well on highly structured images not on simply structured images. If the system follows edge specific system alone, it fails to guarantee robust kernel estimation and work well with simple textures, fail to handle highly textured images. So both edge specific and non-edge specific method has its own prons and cons. In NEAS, a combination of both methods are used, i.e edge specific and non-edge specific method.

3.1 Marginalization method

1) Non-Edge specific scheme: The non-edge specific [1][2][3][15] scheme does not rely on the recovery of one specific kind of edge. This consequently avoids the weakness exhibited by the edge specific scheme. A robust solution is the marginalization method, which solves k by maximizing p(k|y). This can be achieve achieved through marginalizing the sparse distribution of x. Its performance is very not stable, because the variation of the sparse priors over different images. For example, a sparse prior distribution learned from highly structured images may fails for simply structured images.

3.2 LSED prediction-based method

1) Edge specific scheme: The edge specific scheme [5][7][8][14] depends on the prediction and detection step edges. LSED detection-based methods assume that sharp explanations are favored around step edges (i.e.sharp edges have lower energy than their blurred versions. This assumption is applicable to only small number of windows that lies at region close to LSED. The LSED prediction-based methods firstly restore sharp step edges and then use them to estimate a good initial kernel, which traps the optimization into the local minimum corresponding to the sharp solution. The most commonly used approach to restore step edges is the shock filter. Since sharpening filters that includes the shock filter can only restore step edges, the LSED prediction-based methods cannot handle images in which the number of LSEDs is small, e.g. highly textured images.

3.3 Algorithm

This shows the basic iteration process of NEAS[10].

The marginalization method: iterating 1, 2 and 3 for five times

1) Update weights: Wγ(i,i)=Σj(ωi,γ,j/σ2 j) with

ωi,γ,j0=(Πj0 σj0 exp(−E(kfi,γk2) 2σ2 j0)(Σj Πj σj exp(−E(kfi,γk2) 2σ2 j))

2) Update C and xm:C(i,i)=1/Ax(i,i) and Axxm=bx with Ax= 1 σ2 n TT k Tk +ΣγTT fγ(Wγ + 1 σ2 R)Tfγ and bx= 1 P2 n TT k y+ 1 σ2 R diag(VM)σy(TT fγ(fγ(xl)) where Tk,Tfγ and VM denotes the block Toeplitz matrixes of k, fγ and M,and diag() produces a diagonal matrix.

3) Update k:solve mink 1 2kT Akk − bT k k s.t k⩾0 with Ak(i1,i2)=Pixm(i+i1)xm(i+i2)+C(i+i1,i+i2) and

bk(i1)=Pixm(i + i1)y(i).
LSED prediction-based method:iterating 4,5 and 6 for five times
4) Sharpen the LSED of xm using filter.
5) Update xl: minx 1 2σ2 nkk⊗x-yk2+ 1 2σ2 RPγ kfγ(x)-M ◦fγ(xm)k2 +Pγ kfγ(x)kα
6) Update k: minx 1 2σ2 nkk⊗x-yk2 + kk'α

3.4 NEAS

NEAS works as an iterative process that alternates between the marginalization method and the LSED prediction-based method. The former provides a good initial value and a regularization term for the latter. The latter provides an adaptive prior for the former. In this manner, the marginalization method and the LSED prediction based method are regularized by each other. The enhanced robustness in NEAS can be explained from the perspective of energy minimization. Essentially, the marginalization method provides a better initial value and an energy constraint which allow the LSED prediction-based method to adaptively cope with image diversity. To achieve this, the initial value must be placed within a small neighborhood of the local minimum for the true sharp solution and hence allow the local-minimum based method to converge at the desired position.

NEAS adopts the result of the marginalization method as the initial value. The initial values of the traditional LSED prediction based methods are obtained from the shock filters. They are edge sensitive and can be very far from the true solution. This is particularly true for images with complex textures. The better initial value from the marginalization methods improves the result significantly. Also, through the designed iteration, the results of the marginalization are used as a constraint to prevent the LSED prediction-based method from drifting away from the true solution. Such a drift occurs very frequently in LSED prediction-based methods due to inaccurately recovered narrow edges. The new constraint allows the sharp solution to remain as a good local minimum.

3.5 WORKING

A blurred input is given to the system. It first iterates in marginalization method of non-edge specific scheme. First three steps follows the marginalization method mentioned in [3]. Adopted Levin et al.s EM optimization [3] to solve for k.

1) Marginalization Stage: To optimize the MAPk score, an Expectation-Maximization(EM) framework will treat the updated interim latent updated image as a hidden variable and it tries to marginalizes values over it. In brief, this algorithm iterate between two main steps. If the kernel is estimated efficiently half job is done. The E-step corresponds that, it solves for a mean best image following a non-blind deconvolution problem keeping k constant, and also finding the covariance around mean image. M-step corresponding to one which solves for the best kernel from the image from the E-step. Calculation of the covariance is the crucial difference difference between the EM MAPk approach from the MAPx,k approach.

2) Variational Free Energy Strategies: In closed form the mean and covariance of sparse prior computation is difficult. This is done using a even simpler approach that is use of variational strategies for optimization. When k is known it is a non-blind deblurring method, so when k is known a mean image estimate μ is computed using iterative reweighted method. In each iteration, one finds μ by solving an NN linear system Axμ = bx. This system seeks μ minimizing the error and a weighted regularization term which is applied to derivatives. A upper bound must be provided on MOG negative log likelihood by the selection of weights to provide a quadratic bound based on the earlier μ solution. This reweighted iterative least squares algorithm is a standard technique for calculating x. To powerfully compute the covariance around the mean x (image) μ, then approximate it with a diagonal matrix. Given μ,C, one employs the M-step, and kernel can be solved using a quadratic problem solution. Following the EM optimization in [3] has several difficulties, the result generated from marginalization has to go through many iterations more than that of mentioned in the base paper. But too many iterations make the system really slow. Its taking too much time for getting preferred output. So, for getting the estimated kernel and the updated images , one should wait so long.

3) Prediction Stage: The output from the previous stage is given as input to this stage i.e estimated kernel and the updated image. This will give better prior for kernel. In algorithm it is mentioned to use shock filter for edge detection. But using shock filter doesn't produce the desired result. A similar approach is used with derivative filters and also an wrap boundary function is added to correct image boundary. Next step is the xl calculation. Also adopted ideas mentioned in [7] and [8]. When implemented the system found to be time consuming. But the quality of deblurred image is high even though it is time consuming. For convenience and to make the system even faster the number of iterations reduced and found the system comparatively less time consuming than before.

IV. EXPERIMENT ANALYSIS

To show the effectiveness of the proposed method, a test on five state-of-the-art blind deconvolution algorithms using large dataset [13], including Fergus et al.[1], Levin et al. [3], Krishnan et al. [4], Cho et al. [7] and Xu et al. [9] is performed. Figure 1 [10] shows the comparison results. For the clarity of viewing, we only show the best result of the previous algorithms for comparison. The proposed algorithm performs effectively than the other. We demonstrate the effectiveness of our method by testing it on a large standard testing data set of Levin et al. [3] many other challenging images with various and quite large blurs for conducting experiments.

Figure 2(a) shows the blurred input image. The output of marginalization stage is shown in Fig 2(b) which is the updated image, i.e is the deconvolution result from non-edge specific method and Fig 2(c) show the estimated kernel at this stage. Marginalization method fails when it comes to simply structured image at the same time it work well for highly structured image. For the efficient working of blind deconvolution algorithms a strong prior is required. The estimated kernel and the final output image from the marginalization step is given as the initial kernel and input image for LSED predication step. We have reduced the iteration to 3 which make the faster output from marginalization step than one mentioned in [9]. In the prediction step we have used combinations of two edge specific concepts [7], [8], [10]. In this stage edges are detected using a derivative filter[7], later it perform iterative update of image 'x' and kernel 'k'. Output from NEAS approach in each stage is given in it. The iteration between in term latent image and the kernel is shown in Figure 2(d) which is edge specific scheme. Final output of NEAS is given in Figure 2(e) and 2(f) that is the output image and estimated kernel respectively.

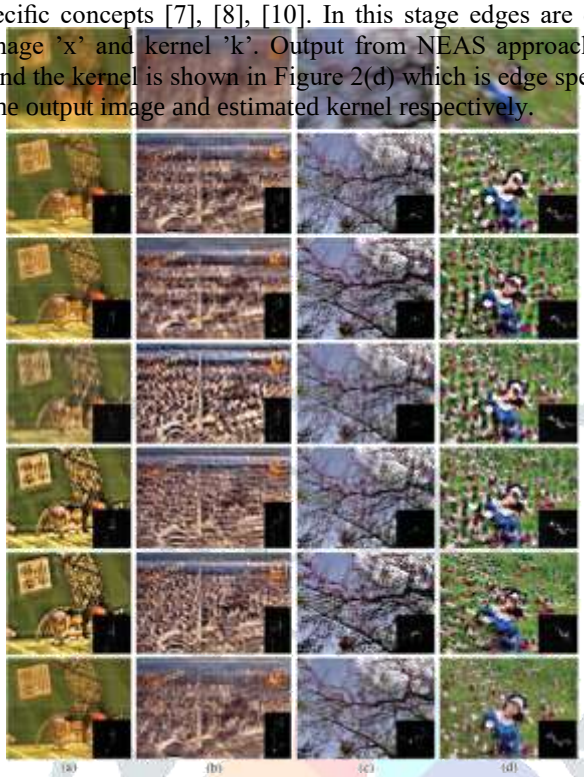

Fig. 1. Comparison with existing deblurring methods. The results by Xu et al. [18], Cho et al. [17], Fergus et al. [9], Levin et al. [25], Krishnan et al. [24], and by our method are shown. (a) and (b) Two images, which contain many large step edges. (c) and (d) Two images, which lack step edges.

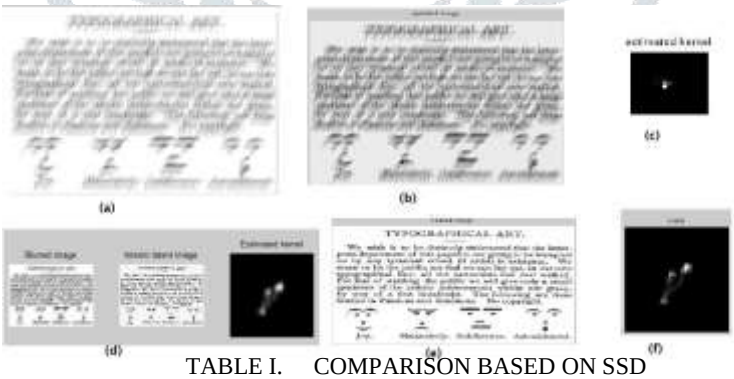

TABLE I. COMPARISON BASED ON SSD

Error Ratio	SSD
Xu et . al	4.41
Cho et . al	9.21
Fergus et . al	2.91
Levin et . al	1.9
Krishnan et . al	3.07
Proposed (NEAS)	1.23

To assess the accuracy of the estimated kernels, we follow Levin et al. [2][11] by usage of sum of squared differences (SSD) ratio between the deconvolution error with the estimated kernel and the deconvolution error with the true kernel. Empirically, SSD ratios below 3 are regarded as visually acceptable. It is assumed that SSD>3 is failure.

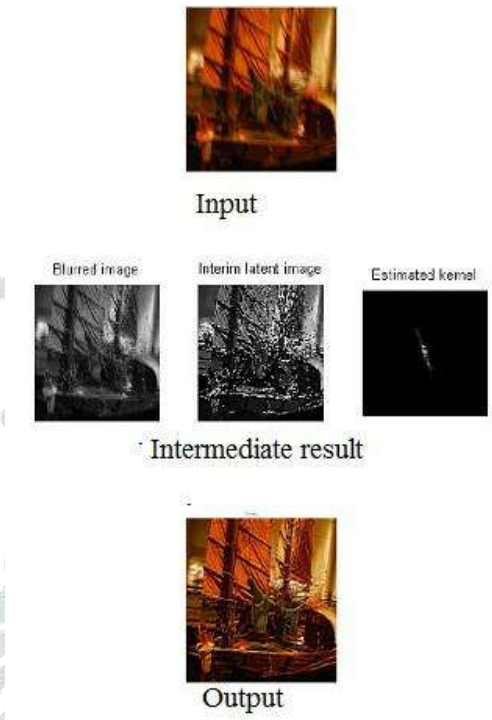

Fig. 3.NEAS output

V. CONCLUSION

NEAS is implemented through a novel prior that combines LSED prediction and prior distribution marginalization. NEAS is implemented as a novel blind motion deblurring method in which the output from marginalization method is given to LSED predication method in order to detect sharp edges and there by producing high quality result. Also, like most other blind motion deblurring methods, it do not consider common photographic artifacts, such as over and under-exposed regions, non-Gaussian noise and non-linear tone scale. Incorporating these factors into blind motion deblurring will be interesting to future work.

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