COMPARATIVE ANALYSIS OF DIFFERENT DEBLURRING TECHNIQUES

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ABSTRACT

Recovery of a sharp image from blurred one is vital for the user. Blurred image is not acceptable for many scientific applications, such as astronomical imaging as well as consumer photography. Image restoration is used to get the original sharp image from the corrupted data. Blurred images may result from certain camera properties and also due to camera movement. For example, spatially uniform defocus blur depends on depth and spatially varying blur is due to object movements. In this paper, the limitations and potentials of recent methods when dealing with quite large blurs and severe noise are investigated. The different processes and algorithms for deblurring purpose are also compared. Experimental results show that the proposed method improves picture quality by removing various types of noise present in the image.

Keywords: **Bayesian estimation, CODA, Deterministic filter, MAP**

I. INTRODUCTION

Digital photography has immense applications in different fields ranging from medical to engineering to various crime investigations. It is important that the captured image is clear enough to get the complete information from the image. But sometimes improper camera settings or manual mistakes lead to blurred image and its characteristics may get changed depending upon the percentage of noise added in the image. In order to make the image sharp and clear, various mathematical models are employed and this process is known as “Image Deblurring”.

There are various image deblurring methods with the help of which blurred image can be converted into clear image. Although tremendous progress has been recently made, the results for quite large blurs (blur kernels of 100 pixels and larger) and severe noise are still far from perfect. In this paper the three most widely used methods are implemented and compared for their blur reducing efficiency. The three deblurring methods compared are deterministic filter method, Bayesian estimation method and CODA.

II. LITERATURE SURVEY

Blur which arises due to camera wobble is common in consumer-level photography. It occurs when a long disclosure is essential and the camera is not held still. As the camera movement progresses, the image formation process integrates a stream of photographs of the scene taken from slightly different viewpoints. Extracting blur arisen due to shaking of camera is currently a very active area of research. Given only a single photograph, this blur removal is known as blind deconvolution that is concurrently recovering both the blur kernel and the deblurred, sharp image.

Software-based methods use image priors and kernel priors to constrain an optimization for the blur kernel and the latent image. Fergus et al [6] recuperated a blur kernel by using a natural image prior on image gradients in a variation Bayes framework. Shan et al [12] integrated spatial parameters to enforce natural image statistics using a local ringing suppression step. Osher et al [7] used transparency maps to get cues for object motion to recover blur kernels by performing blind deconvolution on the alpha matte, with a prior on the alpha-matte. Joshi et al [5] predicted a sharp image that is consistent with an observed blurred image. Levin et al [9] gave a nice overview of several of these existing deblurring techniques. Common to all of them is that they assume spatial invariance for the blur. Levin et al showed that spatial invariance is often violated, as it is only valid in limited cases of camera motion.

Motion blur model is generally used in deblurring techniques which is described here. Let I be the latent image of a constant depth scene and b be the recorded blurred image. The blurred image can be written as a convolution of the latent image with a kernel, k and the addition of some noise, n:

$$b = k \otimes l + n \qquad (1)$$

This convolution model does not account for variations in depth and view-dependent illumination changes and we do not handle them here. This model can also be written as matrix-vector product:

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

where, L, B, and N denote the column-vector forms of l, b, and n respectively. K is an image filtering matrix that applies the convolution each row of K is the blur kernel placed at each pixel location and unraveled into a row vector. For this reason, we also refer to K as the blur matrix. With spatially invariant blur each row has the same values that are just shifted in location. This matrix-vector form becomes particularly useful for formulating spatially varying blur as each row contains a different blur kernel for each pixel.

III. DETERMINISTIC FILTER METHOD

The deterministic filter can be defined as deterministic function F of the input blurred image I: $F(I) = L$ with denoting the output sharp image. One of the most well-known approaches in this paradigm is un-sharp masking [3], which reduces the low frequency first, and then highlights the high-frequency components. The performance of deterministic filter method changes according to the selection of high-pass filters and the adaptive edge weights [9]–[12]. This approach assumes that the blurred edges do not drift too far away from the latent sharp edges; thus, it can handle only the defocus blurs and very small motion blurs.

This approach assumes that the blurred edges do not drift too far away from the latent sharp edges; thus, it can handle only the defocus blurs and very small motion blurs. For very large blurs, the image narrow edges or details are severely damaged and very difficult to restore. A practical solution is to detect and restore large step edges explicitly or implicitly, which we call the step-edge-based filter (SEBF) [5]. Explicit SEBF first locates the step edge and then propagates the local intensity extrema towards the edge. Implicit SEBF performs edge detection and restoration in a single step, based on zero crossings of high-pass filters. Commonly used implicit SEBFs include the shock filter [6], the backward diffusion, the morphological filtering, the fuzzy operator and many other adapted versions.

3.1 Limitation of Deterministic Filter method

The deterministic filter has been widely used in sharpening small blurs. The SEBF cannot handle very large blur kernels.

IV. BAYESIAN ESTIMATION

To infer the deblurred image from the posterior, we extend the approach of [15] and in contrast to previous deblurring methods compute Bayesian minimum mean squared error estimate (MMSE). (MMSE) estimate is obtained as the parameter vector that minimizes a mean square error cost function defined as

$$R_{MMSE}(\hat{\theta}|y) = \int_{\theta} (\hat{\theta} - \theta)^2 f_{\theta|y}(\theta|y) d\theta \qquad (3)$$

From Bayes' rule the posterior probability density function of the parameter vector θ given y, $f_{\theta|y}(\theta|y)$), can be expressed as

$$f_{\theta|y}(\theta|y) = \frac{f_{\theta|y}(y|\theta) f_{\theta}(\theta)}{f_Y(y)} \qquad (4)$$

Where for a given observation, $f_Y(y)$ is a constant and has only a normalizing effect and $f_{\theta|y}(\theta|y)$is the likelihood that the observation signal y was generated by the parameter vector θ. The advantage over the more common MAP approach, at least for image de-noising [16], is that that it leads to superior results, both for smooth and textured image regions. Secondly, MMSE estimates yield a higher correlation between the image restoration performance and the generative quality of the model. This on one hand lets us take advantage of powerful learned priors, and on the other hand allows us to work without any regularization parameter that balances the prior and the likelihood, which is very desirable especially when the noise level is not known. The middle flow- chart in Figure 1 illustrates this method. By contrast, the MAP (L, K) estimator is well constrained and can accurately recover the true kernel if the image size is much larger than the kernel size Compared. With the first method, Bayesian estimation has the following advantages:

1) This method is not responsive to local narrow edges because it depends on statistics;

2) If the noise does not create much changes in the statistics of image this method is not sensitive to image noise.

4.1 Limitations of Bayesian Estimation

The MAP and MAP estimators have very similar performance with respect to the same SN. They both belong to Bayesian estimation and should have similar properties. The estimation states that theory states that when the SN is small, the Bayesian estimation will be "biased" towards the prior mean, which, however, is not the true solution in the blind deconvolution case from the perspective of the energy function to understand this limitation.

The first limitation can be overcome by adopting different blur models. For example, by using the same variational Bayes method, Fergus *et al.* [6] address uniform blurs with a simple convolution model, whereas Whyte *et al.* [15] address non uniform blurs with a weighted integral model. The second limitation is very challenging to overcome because it is the latent limitation of Bayesian estimation. We will show that, counter intuitively, the naive MAP estimator and the MAP estimator have similar performance in blind deconvolution and own the same limitation when dealing with very large blurs: Insufficient samples make the global optimum no longer favour the true solution.

V. CONJUNCTIVE DEBLURRING ALGORITHM

In this paradigm, the deterministic filter and Bayesian estimation are performed in a conjunctive manner. The rightmost flowchart in Figure. 1 illustrates the CODA. The works in [11] and [13] can be viewed as two approximations of this paradigm, although the authors might not have motivated themselves in this way. In the work of Cho and Lee, a edge prediction scheme, which is a combination of the bilateral filter and the shock filter together with a simple threshold method, is introduced to remedy the MAP estimator. Xu and Jiaya enhance the work of Cho and Lee by proposing a gradient selection algorithm in order to exclude the narrow edges, which cannot be restored by the shock filter. The resultant methods can handle challenging examples beyond the capability of the first and second paradigms. Unfortunately, the latent reason why this paradigm can handle quite large blurs beyond Bayesian estimation is not given in either the work of Cho and Lee or that of Xu and Jiaya.

The adaptive tonal correction algorithm presented here uses the low- exposure or darker looking image as its input and enhances its appearance via tonal correction by making use of the mean (brightness) and variance (contrast) of the original blurred image in an adaptive manner. The main contribution here thus consists of an automatic process by which the tonal correction is done. The following tonal curve equation is considered in our algorithm is:

$$f(x) = \frac{1}{\log x} \tag{5}$$

Whereas a parameter altering the contrast level. The optimum value of is taken to be the one that makes the contrast of the enhanced image equal to the contrast of the blurred image. To obtain the optimum parameter values in a computationally efficient manner, the binary search approach is used.

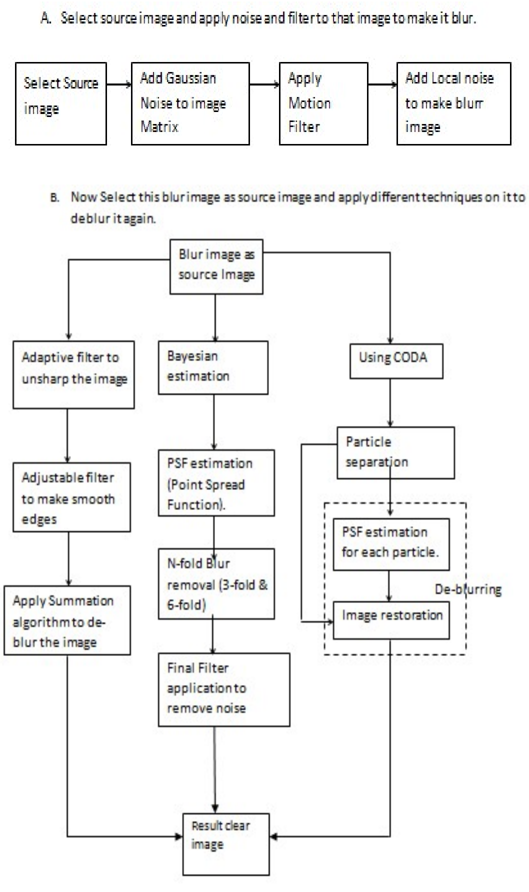

Figure 1: Block diagram of proposed work

4.1 LIMITATIONS OF CODA

Deterministic filters cannot recover the narrow edges totally damaged by the blur. Bayesian estimation with the strong aware prior is capable of recovering the narrow edges only if a reasonably accurate kernel is available. In CODA, the temporal kernel is computed by using the large step edges restored by the deterministic filter. Therefore, if the image structures are dominated by narrow edges, CODA cannot produce an accurate blur kernel and for these types of images the result of Bayesian estimation is better than CODA. This problem is also faced by other CODAs. Texture hallucination techniques [16] might be adopted to restore the narrow edges. Our algorithm does not consider a number of common photographic effects, such as saturated pixels from strong lights, underexposed regions in very dark environments, and nonlinear tone scale. Incorporating these factors into our model will be an interesting future work.

VI. RESULTS

The software used for this implementation is MATLAB version 10 or above. As the algorithm states that the image first converted to blur one and then applying three different techniques we recovered the image with different property values. Block diagram of all the techniques is shown in Figure1.

The first output step after making image blurred is shown in Figure 2.

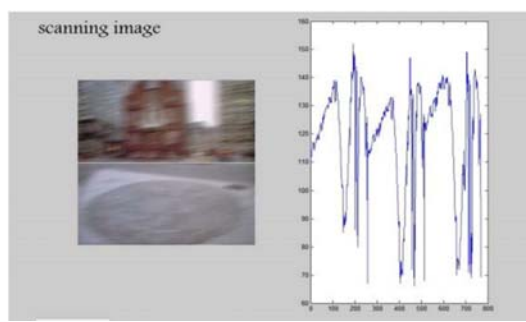

Figure 2: Scanning of image

After scanning the image, different techniques have been applied on it and the property values in each case are calculated as shown in Figure 3.

The values in tabular format are shown in Table 1.The results are shown in graphical format in Figure 4(a) and 4(b). This graph shows the error on y axis and number of iterations on x axis. The errors are PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error).

Figure 3: 10 CODA iterations for calculation of image properties

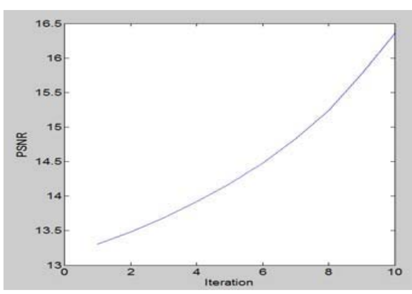

Figure 4(a): Variation of PSNR in CODA

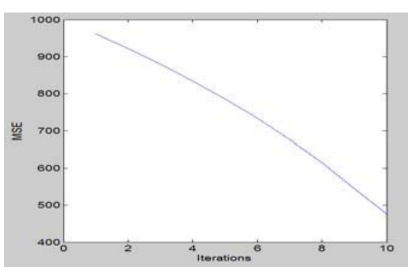

Figure 4(b) Variation of MSE in CODA

The results in tabular format are shown in Table 1.

Table 1: Comparison of three methods in terms of MSE and PSNR

Image	Property	Deterministic Filter	Bayesian Filter	CODA
Bridge.png	MSE	90.16	112.03	98.04
	PSNR	22.76	34.96	39.03
Veggies.png	MSE	56.33	177.61	36.92
	PSNR	25.32	32.71	60.06

Figure 5: Final result of each method

The deblurred image with values of PSNR and MSE of each method is shown in Figure 5.

VII. CONCLUSION

Three methods of image deblurring viz., Deterministic filter method; Bayesian estimation method and CODA have been implemented on different colour images. A detailed study of these methods has evolved that each method is good on its own and provides quite good results in some particular conditions but a comparative analysis shows that for the same image CODA provides much better result than deterministic and Bayesian method. CODA also has some limitations. CODA results are not much appreciated when image is dominated by narrow edges.

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