Research Paper Engineering

Alpha Rooting for Image Deblurring

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ABSTRACT

To recover a sharp version from a blurred image is a long-standing inverse problem. In this paper, we analyze image deblurring in both theoretically and experimentally through three paradigms are: 1) The deterministic filter2) Bayesian Estimation 3) The proposed algorithm, alpha tonal correction methods, which gives better performance than the deterministic filter and sharp image estimation. We point out the weaknesses of the deterministic filter and unify the limitation latent in two kinds of image estimation methods. We further explain proposed alpha correction method which can able to handle quite large blurs beyond deterministic filter and image estimation. Finally, we demonstrate that our method outperforms state-of-the-art methods with a large margin.

Keywords: Blind image DE convolution, image sharpening, alpha Tonal correction and deterministic

INTRODUCTION

Recovery of a sharp image from a blurred one is a chronic ill-posed problem for many scientific applications, such as astronomical Imaging and consumer photography. Generally, there are many properties of a camera and a scene that can lead to blur, i.e., spatially uniform defocus blur dependent on depth, spatially varying defocus blur due to focal length variation over the image plane, spatially uniform blur due to camera translation, spatially varying blur due to camera roll, yaw and pitch motions, and spatially varying blur due to object movements. In this paper, Our goal is to reveal the limitations and potentials of recent methods when dealing with quite large blurs and severe noise. What are the main challenges and what are the key components that make handling quite large blurs and severe noise possible? What should attract further research efforts in the future additionally; additionally we design a novel deblurring method to handle various large blurs and significant noise. We consider the research on this topic has evolved mainly through two paradigms 1) The deterministic sharpening filter 2)sharpening image Bayesian estimation using blind DE convolution method.in this paper we focus on third paradigm the alpha tonal correction method we next review these Three paradigms by reveling the latent limitations.

First Paradigm:

The Deterministic Filter The deterministic filter can be modeled as deterministic function F of the input blurred image I:F(I)=L,with L denoting the output sharp image. The leftmost flow chart in Fig.1 illustrates the rest paradigm. One of the most well-known approaches in this paradigm is unsharp masking, of which the basic idea is to reduce the low frequency first, and then high-lights the high-frequency components. The performance varies according to the adopted high-pass filters and the adaptive edge weights.

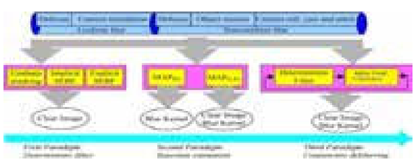

Fig. 1. Three paradigms of the methods to recover the sharp image from a blurred one. The deterministic filter, Bayesian estimation & alpha tonal correction..

of which the basic idea is to reduce the low frequency first, and then high- lights the high-frequency components.The performance varies according to the adopted high-pass filters and the adaptive edge weights. 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).Explicit SEBF rest locates the step edge and then propagates the local intensity extreme toward 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, the backward diffusion and many other adapted versions.

Second Paradigm: Bayesian Estimation

In this paradigm, both the kernel and image are taken as samples from some probability spaces. The goal is to solve for the unknowns that minimize the expected value of a loss function. The most commonly used loss function is the Dirac delta function, which yields the maximum a posterior (MAP) estimator. The center flow chart in Fig.1shows such a second-paradigm approach. Bayesian estimation has been recently hotly discussed because it has led to great progress. The success of it stems from the use of various image priors and estimators. In the MAP (L, K) case, which solves for both the kernel and image simultaneously, and a MAP (L, K) case, which solves for the kernel alone. It has been pointed out that naive a MAP (L, K) estimator fails to yield the desired result since the sparse priors prefer no-blur explanations. Current MAP estimators avoid the trivial solution by integrating many additional components, such as sharp edge detection iterative likelihood update and sparse representation under frame let and curvelet system. By contrast, the MAP (L, K) estimator is wellconstrainedandcan accurately recover the true kernel if the image size is much larger than the kernel size Compared. With the first paradigm, Bayesian estimation has the following advantages:

1) The approach is not sensitive to local narrow edges because it depends on statistics,
2) It is not sensitive to image noise if the noise is not too much to change the statistics.

Sharp image Estimation

The blurring process is formulated as an invertible linear system, which models the blurry image as the convolution of a sharp image with the imaging system's PSF.Thus, if we know the original sharp image, recovering the kernel is straightforward. The key contribution of our work is a reliable and widely applicable method for predicting a sharp image from a single blurry image.

Blind Estimation

For blind sharp image prediction, we assume blur is due to a PSF with a single mode , such that when an image is blurred, the ability to localize a previously sharp edge is unchanged; however, the strength and profile of the edge is changed. Thus, by localizing blurred edges and Predicting sharp edge profiles, locally estimating a sharp image is possible. We assume that all observed blurred edges result from convolving an ideal step edge with the unknown kernel. Our algorithm finds the location and orientation of edges in the blurred image using a sub-pixel difference of Gaussians edge detector. It then predicts an ideal sharp edge by finding the local maximum and minimum pixel values, in a robust way, along the edge profile and propagates these values from pixels on each side of an edge to the sub-pixel edge location. The pixel on the edge itself is colored according to the weighted average of the maximum and minimum values according to the distance of the sub-pixel location to the pixel center, which is a simple form of anti-aliasing.

Non-Blind Estimation

For non-blind sharp edge prediction, we want to compute the PSF given that we know the sharp image. Since we anticipate using this technique in a controlled lab setup, we designed a special calibration pattern for this purpose. We take an image of this pattern and align the known grid pattern to the image to get the sharp/blurry pair needed to compute the PSF accurately. The grid has corner features so that it can be automatically detected and aligned, and it also has sharp step edges equally distributed at all orientations within a tiled pattern, so that it provides edges that capture every radial slice of the PSF because our corners are actually balanced checkerbo ardcrossings,theydonotsufferfrom"shrinkage"due to blurring. Once corners are found, the ground truth pattern is aligned to the acquired image..

Limitations of the first paradigms

The deterministic filters have been widely used in sharpening small blurs. The SEBF can handle very large blur kernels. We take the shock filter as an example, i.e.

$$I^{(t+1)} = I^{(t)} - sign(\Delta I^{(t)} \| \nabla I^{(t)} \|_{1} dt)$$

where $I^{(t)}$ is an image at time, Δ is Laplacian operator, and dt is the time step for a single evolution. The shock filter sharpens image at inflection points (zero crossings of the second derivative), thus depending on image local features rather the SN.The local extreme of remain unchanged in the evolutions. Fig. 2 gives two small images blurred by large kernels. Although it is intuitively correct that Bayesian estimation can handle most blurred images, experiments of the aforementioned MAP estimators have shown that the performance is not always stable, sometimes even worse than the deterministic filters. The unstable performance gain is due to the following reasons:

1) A Bayesian estimator is built for a specific blur model and cannot handle other types of blurs without adaptation, and
2) The performance highly depends on the SNs and statistics.

Limitations of Bayesian Estimation:

Fig. 2 demonstrates that 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 theory states that when the SN is small, the Bayesian estimation will be "biased" toward the prior mean, which, however, is not the true solution in the blind de- convolution case. From the perspective of the energy function to understand this limitation.

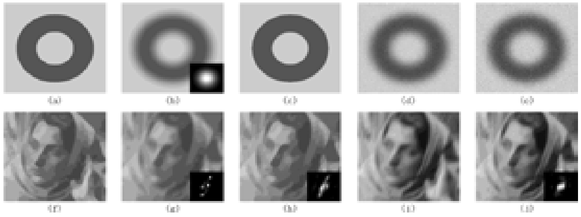

Fig. 2. (a) Original sharp image. (b) The blurred image without noise. The Gaussian kernel is produced by MATLAB with special ("Gaussian", 61, 11). (c) The recovered image from (b) by the shock filter. (d) The blurred image with large noise. (e) The recovered image from (d) by the shock filter. (f) The original sharp image without narrow edges. (g) The blurred image and the kernel. (h) The recovered image from (g) by the shock k filter. PSNR

ALPHA TONAL CORRECTION

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:

$$f(X) = \frac{\log(ax - x + 1)}{\log x} \qquad (2)$$

Whereas x denotes pixel values of the input image, and the α is a parameter altering the brightness α s level. The optimal value of α is considered to be the one that makes the brightness of the enhanced image equal to the brightness of the blurred image This correction also improves the image contrast. To further improve the contrast, a second tonal correction curve can be used to match the contrast of the blurred image. Among various possible curve functions.

$$g(x) = \frac{\arctan(\beta(f(x) - 0.5)) + 0.5)}{2\tan(\beta/2)} - (3)$$

Whereas β a parameter altering the Contrast level. The optimum value of β 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.

CONCLUSION

Recovery of the sharp image from a blurred one is an important and long- standing problem for many applications. In this paper, we have rest analyzed the potentials and limitations latent in recent methods when handling quite large blurs and significant noise. While our method. out performs state-of-the-art methods both in robustness to noise and the capability of handling quite large blurs, it is still limited by the images dominated by narrow edges. Recovering the totally damaged narrow edges is still a very challenging problem faced by state-of-The-art methods and should attract further research efforts.

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