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An Adaptive Technique for Restoration of Real Blurred Images under Unknown Conditions

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Abstract-* Recently, a normalized image prior was proposed so that the global minimum would not correspond to the blurred image. Multi-resolution approaches, which avoid some local minima, were recently proposed. Good local minima can also be found by using continuation schemes, where the regularizing parameter is gradually decreased. A recent come within reach of although not requiring previous in arrange on the blurring sift achieves high-tech recital for a wide range of real-world BID tribulations. In this paper, we improve upon the method of. We fully embrace the UBC, without an increase in computational cost, due to the way in which we use the alternating direction method of multipliers (ADMM) to solve the minimizations required by that method. We propose a new version of that technique in which both the optimization tribulations with respect to the unknown image and with respect to the anonymous blur are solved by the irregular direction technique of multipliers(ADMM) – an optimization tool that has recently sparked much interest for solving inverse problems, namely owing to its modularity and state-of-the-art speed. Furthermore, the convolution operator is itself typically ill-conditioned, making the inverse problem extremely sensitive to inaccurate filter estimates and to the presence of noise. The results are shown in MATLB Platform effectively.

Keywords: Deblurring, multipliers, image, restoration quality

I. INTRODUCTION

The field of image processing is broad and contains many interesting applications. Some of the common image processing areas are image restoration, compression, and segmentation. Many times, the size of the raw data for the images can require gigabytes of data storage. Researchers have developed routines to compress an image into a reversible form to save storage space. In this area, there are methods for the compression via wavelets, using general compression schemes that are applicable to any type of file, and methods which allow some loss of data. The area of segmentation distinguishes objects from the background in an image. This is particular useful for satellite imagery from an intelligence standpoint. It is also useful for identification purpose by using facial imagery in a database. Segmentation is used in robotics, where it is important to locate the correct objects to move or manipulate. Another area of image processing is image restoration. In image restoration, a distorted image is restored to its' original form. This distortion is typically caused by noise in transmission, lens calibration, motion of the camera, or age of the original source of the image. We focus on image restoration in this dissertation. Within image restoration, there are many tasks that researchers consider.

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There has been significant work on denoising, where noise is removed from the image. This noise could be from transmission problems or due to some atmospheric problem at the time the image was captured. There is image inpainting, which recovers missing areas from an image. These missing regions may occur because of age of the original object that was photographed, or physical defects in the object. Another area in restoration is image deblurring. In this area, the objective is to recover the true image given a blurry image. We will focus on image deblurring in this dissertation. There are many models for images. For example, there are wavelet based approaches.

II. IMAGE DEBLURRING

One problem we consider is recovering the true image from a blurry and noisy observed image. It is also known as the image deblurring problem and has been studied for known and unknown blur kernels. We focus on the blind deconvolution dealing with unknown kernels. The blind deconvolution problem has been studied by various researchers using different approaches. There are approaches using functional settings with different types of alternating minimization schemes. You and Kaveh considered using an alternating scheme involving the H1 norm for the kernel. Building on You and Kaveh's work, Chan and Wong extended their idea to the TV norm for both the image and the kernel, noting that in many cases the kernel function has sharp edges (such as motion blur and out of focus blur). The authors used the Alternating-Minimization method for image and kernel recovery. Lin, et. al., extended the TV functional to include additional constraints on the kernel in the problem and used Bregman iteration to improve the result. More recent works deal with spatially variant blurs and non-local functional. Another approach for deblurring is to apply various filtering techniques. Fish et. al. considered using the Richardson-Lucy algorithm to implement an alternating mini- mization scheme using Bayes's Theorem, and got improved results from Weiner filter blind deconvolution. Using partial differential equations is proposed by Osher and Rudin via shock filter. This method reconstructs the edges by creating shock at inflection points and finds accurate edge locations. Alvarez and Mazorra considered a similar approach but pre-conditioning the image with diffusion in order that it can handle denoising and deblurring simultaneously. Gilboa, et. al extended this idea by using a complex diffusion process to be robust against noise. There is considerable work on combining several functionals in various image processing tasks. Chan, et. al, in considered using blind deblurring with inpainting, and calculated the solution as a single method.

Bar, et. al., in considered coupling with an edge detection for Gaussian type kernels. The authors used the L1 fidelity term to remove salt and pepper noise in a deblurring problem. The authors considered deblurring and impulse noise removal via a combination of the Mumford-Shah model and total variation models in a multichannel setting, and in the authors combined semi-blind image restoration

$$\min_{k,u} \|k \star u - u_0\|^2_{L^2(\Omega)} + \lambda_1\|k\| + \lambda_2\|u\|$$

with segmentation for parametric blur kernels. Given the quantity of research in the area, Chan and Shen present an overview of image deblurring methods developed over the past two decades, which includes stochastic methods, Tikhonov regularizations including TV regularization, and wavelet based algorithms. We focus on the model of You and Kaveh and Chan and Wong which is to consider minimizing the functional. Blind image deblurring(BID) is an inverse problem where the observed image is modeled as resulting from the convolution with a blurring filter, possibly followed by additive noise, and the goal is to estimate both the underlying image and the blurring filter. Clearly, BID is a severely ill-posed problem, for which there are infinitely many solution. Furthermore, the convolution operator is itself typically ill-conditioned, making the inverse problem extremely sensitive to inaccurate filter estimates and to the presence of noise.

III. BLIND IMAGE DEBLURRING

Blind image deconvolution techniques restore the original sharp image from an observed degraded image without precise knowledge of a point-spread function (PSF) [43]. There are two main approaches to this: 1) first estimate the PSF, and then apply a non-blind deconvolution method with that PSF; 2) iteratively estimate the PSF and the original sharp image. For the approach that estimates the PSF first, some traditional methods payed attention to the frequency zero patterns in a blur kernel. For example, the Fourier transform of a box function as shown is given as h(ωx , ωy) = sinc(Lωx), meaning that it has periodic zeros at ωx = kπ /L for a non-zero integer k. From, we can expect that the Fourier transform of the observed image has the same zero pattern if we canignore noise. However, such methods are not practical in the presence of noise. Another approach is to take a set of candidate PSFs, and to choose the one that best explains the observed image. The selection criteria differ from method to method, such as residual spectral matching and generalized cross validation. For the approach that iteratively estimates the PSF and the sharp image, Ayers and Dainty proposed to iterate the process of updating the PSF from the estimated sharp image in the Fourier domain, imposing image space constraints on the PSF (non-negativity, for example), updating the sharp image from the PSF in the Fourier domain, and imposing constraints on the sharp image. More recent methods took a conceptually similar approach and estimated a camera shake PSF from a single image by incorporating natural image statistics. Fergus et al. imposed sparseness prior for image derivative distributions and used an ensemble learning approach to solve the otherwise intractable optimization problem. Shan et al. introduced a more sophisticated noise model and a local smoothness prior.

IV. PROPOSED METHOD

Fig3.1 shows four stages in a generic processing flow of image deblurring. We first capture an image, and then segment the image into regions each of which can be assumed to have a uniform blur. After that, for each local region, we estimate the blur kernel and finally use it to deconvolve the image. Some methods may perform segmentation and blur estimation simultaneously. Some may iterate blur estimation

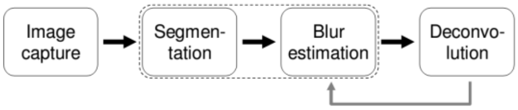

Fig 1: Processing flow of image deblurring

Table 1.1 summarizes the relationship between the proposed method and some of the previous work for three of the above four stages and for the three blur types, namely defocus, motion, and camera shake blur. We set aside the image capture stage because it is trivial for methods purely based on an image processing approach, and for methods involving optics modifications, the (modified) image capture stage can facilitate one, two,or all of the succeeding three stages depending on the methods. Therefore, the table has two rows for each blur type, one for methods involving optics modifications, and the other for pure image processing methods.

Table 3.1 Summary of the relationship between the proposed method and some of the previous work.

		Segmentation	Blur estimation	Deconvolution
Defocus blur	Modified optics	Wavefront coding [27]		Chapter 3
		Coded aperture [48, 90]		
	Image processing	Ozkan et al. 1991 [72]		WaveGSM [15] *
Motion blur	Modified optics		Motion-invariant photography [51]	
			Coded exposure photography [75, 4]	
	Image processing	Chapter 4		(common to the above field *)
		Levin 2006 [47]		
Camera shake blur	Modified optics	Not required	Ben-Ezra and Nayar 2004 [12]	Image processing alone will suffice
	Image processing		Fergus et al. 2006 [28]	(common to the above field *)

Chapter 2

after they are captured, so that she/he can not only obtain an all-in-focus image but also create images focused to different depths. To our knowledge, techniques that synthesize refocused images from a single conventional photograph have not been reported in the literature. While a method for segmenting and identifying 1D motion blur (e.g., horizontal motions) in a single image is reported in the literature, it still seems difficult to handle general 2D (i.e., in-plane) motions in a pure image processing framework. This proposes to move the camera image sensor circularly about the optical axis during exposure, so that the attenuation of high frequency image content due to motion blur can be prevented, facilitating deconvolution.

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This is an extension of motion-invariant photography so that it can handle 2D linear object motion, although that leaves the segmentation stage an open problem. The most closely related work to the proposed approach includes coded exposure photography and motion-invariant photography . Table 1.2 summarizes qualitative comparisons among these methods and ours. Refer also to for detailed comparison between the coded exposure and motion-invariant strategies. The motion-invariant strategy best preserves high frequencies for target object motion range, but it does not generalize to motion directions other than the one it assumes. The coded exposure strategy can handle any direction, and its performance only gradually decreases for faster object motion. Our circular motion strategy can treat any direction and speed up to some assumed limit, and it achieves better high frequency preservation for target object speed than the coded exposure strategy in terms of deconvolution noise. Similar to the motion-invariant strategy, the circular motion strategy degrades static scene parts due to sensor motion, but it can partially track moving objects so that they are recognizable even before deconvolution. Unlike the other strategies, the circular motion strategy has no 180◦ motion ambiguity in PSF estimation; it can distinguish rightward object motion from leftward one. We propose using ADMM to tackle each of the inner minimizations in Algorithm 1 (lines 3 and 4), with Cλ(x,h)as defined in (1). Of course, for q<1, the problem is non-convex, thus we have no theoretical convergence guarantees; however, as shown below, the empirical performance of the algorithm is very competitive.

Updating the Image approximation

The image estimate update problem of Algorithm 1 (line 3) can be written in the unconstrained formulation as

$$C_{\lambda}(x,h)=\frac{1}{2}\|y-MHx\|_2^2+\lambda\sum_{i=1}^{m}\left(\|F_i x\|_2\right)^q$$

$$G^{(j)}=F_j,\ forj=1,\ldots m$$

$$G^{(m+1)}=H$$

$$g^{(j)}\left(u^j\right)=\lambda\left\|u^{(j)}\right\|_2^q,\ forj=1,\ldots m$$

The proposed approach was compared against its ancestor [4], in a set of 30 synthetic experiments with two benchmark images(LenaandCameraman),

For most experiments, the proposed method led to considerably higher ISNR, while being more than three times faster; even higher speed-ups are expected if the fixed number of iterations is replaced by adequate stopping criteria.

OUTPUTS

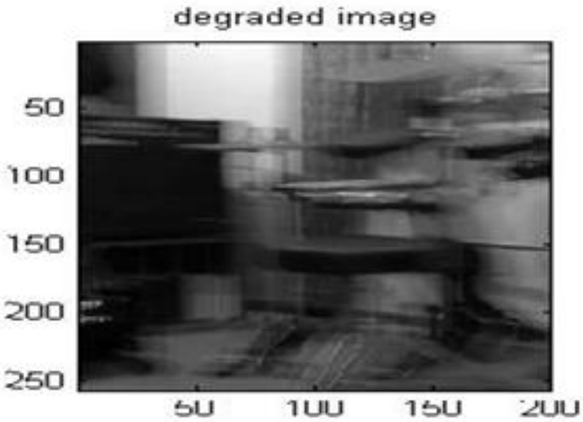

Fig 2. Degra ded Image

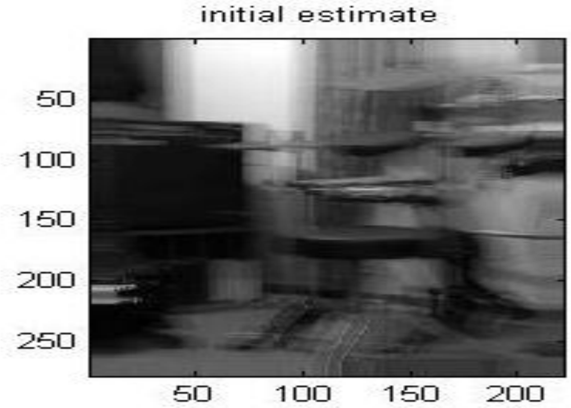

Fig 3. Initial Estimate

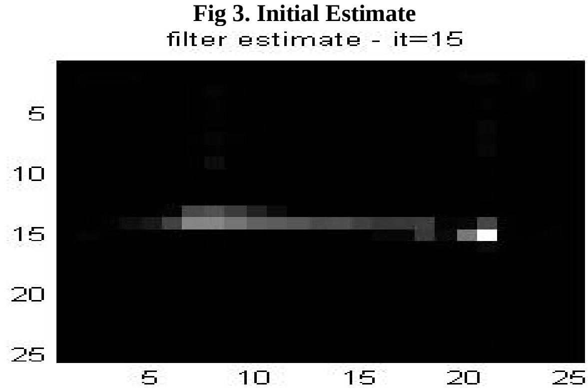

Fig 4. Filter Estimate iterations=15

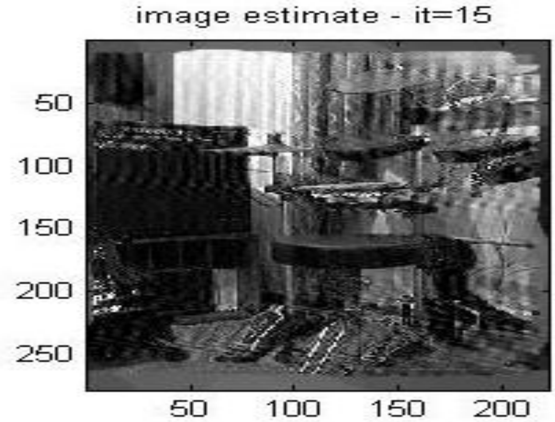

Fig 5. Image estimate iterations=15

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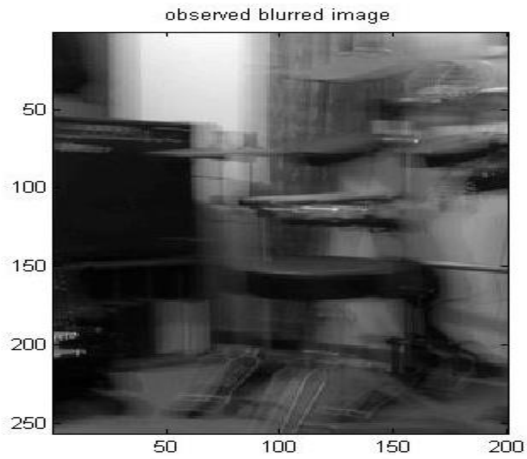

Fig 6. Observed Blurred Image

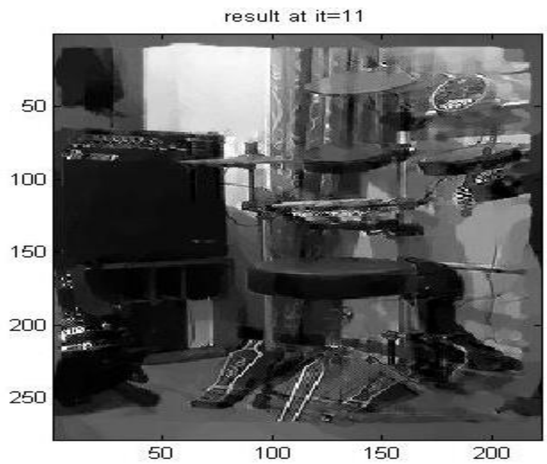

Fig 7. Result of Proposed Algorithm iterations=11

V. CONCLUSION

We have presented a method for removing defocus blur in images in the context of digital refocusing, in which the goal is not only to perform deblurring but also to create images with different focus settings. The proposed method relies exclusively on an image processing approach without camera optics modifications, in order to set a baseline performance achievable without modifying the image capture process. The proposed method consists of a fast image deconvolution method for efficient deblurring, a local blur estimation method which can handle abrupt blur changes at depth discontinuities due to object boundaries, and a set of user interfaces for interactive refocusing.Although the gradient domain approach made the deconvolution process faster, we are no longer able to directly impose positivity constraints on variables, which are known to be effective in regularizing the solution. Currently we fix values after bringing them back to the image domain, but we would like to seek a way to incorporate such constraints into the deconvolution process. Blind image deblurring(BID) is an inverse problem where the observed image is modeled as resulting from the convolution with a blurring filter, possibly followed by additive noise, and the goal is to estimate both the underlying image and the blurring filter. Clearly, BID is a severely ill-posed problem, for which there are infinitely many solution. Furthermore, the convolution operator is itself typically ill-conditioned, making the inverse problem extremely sensitive to inaccurate filter estimates and to the presence of noise. To deal with the ill-posed nature of BID, most methods use prior information on the image and the blurring filter. Concerning the blur, earlier methods typically imposed hard constraints, whereas more recent ones use regularization. Those methods are thus of wider applicability,e.g., to the practically relevant case of a generic motion blur, typically addressed by encouraging sparsity of the blur filter estimate. This paper builds upon the method proposed in [4], which stands out for not using restrictions or regularizers on the blur (apart from a limited support), being able to recover a wide variety of filters. Due to the undetermined nature of BID, direct minimization of the cost functions typically used for deconvolution may not yield the desired sharp image estimates. In fact, these sharp estimates typically corresponds to local (not global) minima of those cost functions. Several strategies have been devised to address this issue, such as the alternating estimation of the image and the blur filter, the use of restrictions, normalization steps, and careful initialization. Recently, a normalized image prior was proposed so that the global minimum would not correspond to the blurred image.

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