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Analysis of Twin with Mysterious Boundaries Using the Alternating Direction Scheme

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Abstract:*Recently, a normalized image prior was proposed so that theglobal minimum would not correspond to the blurred image. Multi-resolution approaches, which avoid some local minima, wererecently proposed. Good local minima can alsobe found by usingcontinuationschemes, where the regularizing parameter is gradually decreased. A recent come within reach of although not requiring previous in arrange on the blurring siftachieves high-tech recital for a wide range of real-worldSID tribulations.In this paper, we improve upon the method of. Wefully embrace the UBC, without an increase in computational cost, due to theway in which we use thealternating direction method of multipliersto solve the minimizations required by that method. We propose a new version of that technique in whichboth the optimization tribulations with respect to the unknown imageand with respect to the anonymous blur are solved by theirregulardirection technique of multipliers– an optimization tool thathas 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 ofthe 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 savestorage 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 whichallow 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 isalso useful for identification purpose by using facial imagery in a database. Segmentation isused 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 distortedimage 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. There has beensignificant work on denoising, where noise is removed from the image. This noise could be from transmission problems or due to some atmospheric problem at thetime the image was captured. There is image inpainting, which recovers missing areas froman image. These missing regions may occur because of age of the originalobject that was photographed, or physical defects in the object. Another area in restorationis image deblurring. In this area, the objective is to recover the trueimage 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.

There are also stochastic based methods for processing images. A more detailed discussion of these and other areas can be found. We focus on aPDE based image model, which is

$$u_0 = k \star u + \eta \qquad (1)$$

The recent rapid popularization of digital cameras allows people to capture a large number ofdigital photographs easily. As the number of casual photographers increases, sodoes the number of "failure" photographs including over/under-exposed, noisy, blurred,and unnaturally-colored images. This situation makes automatic avoidance and correctionof failure photographs important. In fact, automatic corrective functions of digital camerasincluding auto-exposure, automatic white balance, and noise reduction capabilitiessteadily improve to resolve exposure, color, and noise issues.On the other hand, current digital cameras appear to handle image blur only in a limited fashion; they only directly address camera shake blur, but not defocus and motionblur. For camera shake blur, most of the recent cameras are equipped with an anti-camerashake mechanism that moves either the lens or the image sensor to compensate for cameramotion obtained from an accelerometer. For defocus blur, however, although a particularscene depth can be focused with an auto-focus function, objects at different depths cannotbe captured sharply at the same time (depth-of-field effects. Moreover,defocused images can be commonly seen in personal photo collections due to the failure of auto-focusing. In addition, blur caused by object motion, i.e., motion blur can only be avoided by increasing the shutter speed and sensor sensitivitywhen a camera detects motions in a scene, at the expense of an increased noise level.

Screen image deconvolution is an inverse problem where the observed image is modeled as resulting from the convolution with ablurring filter, possibly followed by additive noise, and the goal is toestimate both the underlying image and the blurring filter. Clearly,SID is a severely ill-posed problem, for which there are infinitelymany 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 SID, most methods use priorinformation on the image and the blurring filter. Concerning the blur,earlier methods typically imposed hard constraints, whereas morerecent ones use regularization. Those methods are thus of wider applicability,e.g., to the practicallyrelevant case of a generic motion blur, typically addressed by encouraging sparsity of the blur filter estimate. This paper builds upon the method proposed, which stands outfor not using restrictions or regularizers on the blur (apart from alimited support), being able to recover a wide variety of filters.Due to the undetermined nature of SID, direct minimization ofthe cost functions typically used for deconvolution may not yieldthe desired sharp image estimates. In fact, these sharp estimates typically correspond to local (not global) minima of thosecost functions. Several strategies have been devised to address thisissue, such as the alternating estimation of the image and the blurfilter, the use of restrictions, normalization steps, and careful initialization. Recently, a normalized image prior was proposed so that theglobal minimum would not correspond to the blurred image [5]. Multi-resolution approaches, which avoid some local minima, wererecently proposed [3]. Good local minima can alsobe found by usingcontinuationschemes, where the regularizing parameter is gradually decreased [4]. In a Bayesian framework, it has been claimed that a MAP estimate of the blur filter (aftermarginalizing out the unknown image) is preferable to a joint MAPestimate of the image and the filter [1]. Most blind and non-blind deblurring methods assume periodicboundary conditions (to allow using FFT-based convolutions), instead of the more realisticunknown boundary conditions(UBC) [5]. This incorrect assumption is a problem in non-blind deblurring andbecomes worse in SID (although it has mostly been ignored), sincethe filter estimate is affected by the inaccuracy of the cyclic model.A simple way to evade the UBC problem is to use the “edgetaper”function, which softens the boundaries of the degraded images, reducing the effect of wrongly assuming periodic boundary conditions;this approach is used in [3], while [2] employs a more sophisticated version thereof [1]. Other works on SID [1], althoughnot explicitly reporting it, adopt some strategy for dealing with theboundaries, since they present good results on real blurred images.In this paper, we improve upon the method of [4]. We fully embrace the UBC, without an increase in computational cost, due to theway in which we use thealternating direction method of multipliersto solve the minimizations required by that method.

Screen image deconvolution techniques restore the original sharp image from an observeddegraded image without precise knowledge of a point-spread function (PSF) [43]. Thereare two main approaches to this: 1) first estimate the PSF, and then apply a non-blinddeconvolution method with that PSF; 2) iteratively estimate the PSF and the original sharpimage.For the approach that estimates the PSF first, some traditional methods payed attentionto the frequency zero patterns in a blur kernel. For example, the Fourier transformof a box function as shown is given ash(ωx , ωy) = sinc(Lωx), meaning that ithas periodic zeros at ωx = kπ /L for a non-zero integer k. From, we can expectthat 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. Anotherapproach is to take a set of candidate PSFs, and to choose the one that best explains theobserved image. The selection criteria differ from method to method, such as residualspectral matchingand generalized cross validation. For the approach that iteratively estimates the PSF and the sharp image, Ayers andDainty 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 conceptuallysimilar approach and estimated a camera shake PSF from a single image by incorporating natural image statistics. Fergus et al. imposed sparseness prior for image derivativedistributions and used an ensemble learning approach to solve the otherwise intractableoptimization problem. Shan et al. introduced a more sophisticated noise model anda local smoothness prior.

II. Handling Spatially-Variant Blur

The methods described above all assume a PSF to be spatially-invariant (uniform). Aspatially-variant PSF is usually estimated by sectioning the image and by assuming it tobe approximately spatially-invariant within each section. This means that theblur is assumed to be only slowly varying across the image, as each section should belarge enough to make reliable estimation. This is also true for non-blind spatially-variantdeconvolution methods. A few methods exist that can estimate a spatially-variant PSF with abrupt changesacross the image. Levin identified spatially-variant motion blur by examining the difference between the image derivative distribution along the motion direction and that alongits perpendicular direction for the case of 1D linear motion. You and Kaveh [100] also addressed the problem of removing spatially-variant motion blur, but only a synthetichorizontal motion blur example was presented.Depth-from-focus/defocus techniques generate a depth map of a scene by estimatingthe amount of defocus blurs in images. Hence they can be viewed as spatially-variant PSFestimation methods. Existing methods either use multiple images, or makean estimate at edges in a single image by assuming that a blurred ramp edge is originallya sharp step edge.

For motion blur removal, Raskar et al.developed a coded exposure technique toprevent attenuation of high frequencies due to motion blur at capture time by opening andclosing the shutter during exposure according to a pseudo-random binary code. Agrawaland Xu presented another type of code that enables PSF estimation in addition tohigh frequency preservation. Levin et al.proposed to move the camera image sensorwith a constant 1D acceleration during exposure, and showed that this sensor motion canrender motion blur invariant to 1D linear object motion (e.g., horizontal motion), andthat it evenly distributes the fixed frequency “budget” to different object speeds. That is,objects moving at different speeds can be deblurred equally well.Some researchers proposed to move sensors for different purposes. Ben-Ezra et al.moved the sensor by a fraction of a pixel size between exposures for video superresolution. Mohan et al. moved the lens and sensor to deliberately introduce motionblur that acts like defocus blur. Nagahara et al. moved the sensor along the opticalaxis to make defocus blur depth-invariant.

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

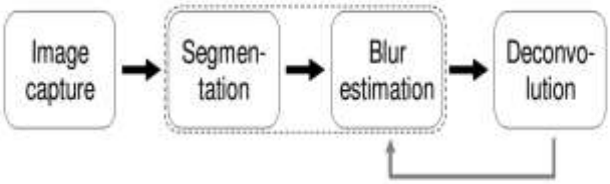
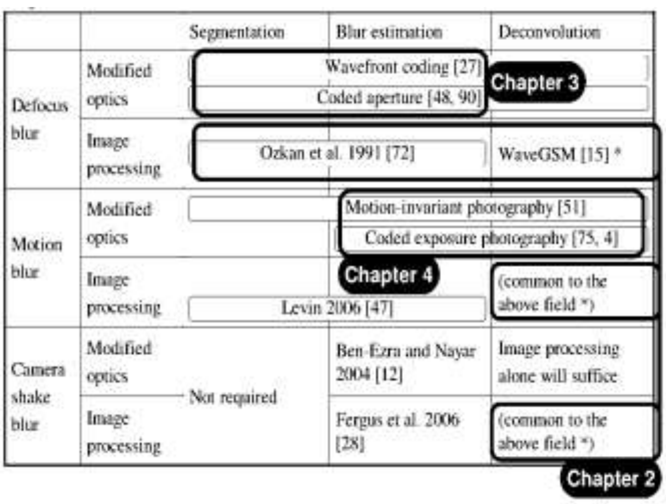


Figure 1: Processing flow of image deblurring

Table 1.1 summarizes the relationship between the proposed method and some of theprevious work for three of the above four stages and for the three blur types, namelydefocus, motion, and camera shake blur. We set aside the image capture stage becauseit is trivial for methods purely based on an image processing approach, and for methodsinvolving 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 hastwo rows for each blur type, one for methods involving optics modifications, and the otherfor pure image processing methods.

Table 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] 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	Levin 2006 [47]		(common to the above field *)
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 *)

After they are captured, so that she/he can not only obtain an all-in-focus image but alsocreate images focused to different depths. To our knowledge, techniques that synthesizerefocused images from a single conventional photograph have not been reported in the literature.

III. Color-Filtered Aperture

Image processing alone does not necessarily producesatisfactory results, and we propose to modify camera optics. We present amethod for simultaneously performing segmentation and defocus blur estimation by placingred, green, and blue color filters in a camera lens aperture. Although wavefront codingcan cover all the latter three stages for image deblurring, it requires special lenses thatcan be expensive, whereas the modification of the proposed method requires only inexpensive color filters. The coded aperture methods also cover the three stages,but some issues remain for the segmentation and blur estimation stages as described. As deconvolution quality can be considerably improved by the coded aperture,this dissertation focuses on facilitating the segmentation and blur estimation stages, andwe use a colorfiltered aperture to exploit parallax cues rather than to directly use defocuscues, which addresses the above-mentioned issues.

The idea of using color filters in the aperture itself has been proposed previously. Fora stereo correspondence measure between the color planes, Amari and Adelsonuseda squared intensity difference with high-pass filtering. As they discussed in their paper,however, this measure was insufficient to compensate for intensity differences betweenthe color planes. Their prototype was not portable, and only a single result for a texturedplanar surface was shown. Chang et al.normalized the intensities within a localwindow ineach color plane before taking the sum of absolute differences between them.But as their camera was equipped with a flashbulb for projecting a speckle pattern ontothe scene in order to generate strong edges in all the color planes, the performance oftheir correspondence measure in the absence of flash was not shown. They also had tocapture another image without flash to obtain a “normal” image. We propose a bettercorrespondence measure between the color planes.As compared to the existing camera designs for single-lens multi-view image capture,our method splits light rays at the aperturesimilarly, but uses only colorfilters as additional optical elements to the lens without requiring multiple exposures.

Although this comes with a price of a reduced number of views (only three) each havingonly a single color plane, we can still obtain useful information for defocus deblurringand post-exposure image editing.As for matting, our method can automatically extract alpha mattes with a single handheld camera in a single exposure, and to the best of our knowledge, such capability hasnot been reported previously.

IV. Motion Blur Removal using Circular Sensor Motion

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. Chapter 4 proposesto move the camera image sensor circularly about the optical axis during exposure, sothat the attenuation of high frequency image content due to motion blur can be prevented,facilitating deconvolution. This is an extension of motion-invariant photographysothat it can handle 2D linear object motion, although that leaves the segmentation stage anopen problem.The most closely related work to the proposed approach includes coded exposure photography and motion-invariant photography . Table 1.2 summarizes qualitativecomparisons among these methods and ours. Refer also tofor detailed comparison between the coded exposure and motion-invariant strategies.

The motion-invariant strategy best preserves high frequencies for target object motionrange, but it does not generalize to motion directions other than the one it assumes. Thecoded exposure strategy can handle any direction, and its performance only graduallydecreases for faster object motion. Our circular motion strategy can treat any directionand speed up to some assumed limit, and it achieves better high frequency preservationfor 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 sceneparts due to sensor motion, but it can partially track moving objects so that they arerecognizable even before deconvolution. Unlike the other strategies, the circular motionstrategy has no 180◦motion ambiguity in PSF estimation; it can distinguish rightwardobject motion from leftward one.

Outputs

The proposed approach was compared against its ancestor [4],in a set of 30 synthetic experiments with two benchmark images (LenaandCameraman), five9×9blur kernels (see Fig. 1), at threenoise levels (BSNR∈{∞,40,30}dB). Instead of periodic boundary conditions, we extended the images with values equal to thenearest boundary and both methods were run assuming unknownboundaries (see Subsection 2.1). For most experiments, the proposed method led to considerably higher ISNR, while being morethan three times faster; even higher speed-ups are expected if thefixed number of iterations is replaced by adequate stopping criteria.The average ISNR and processing times in Table 1 show that theproposed method clearly outperforms the baseline from [4].

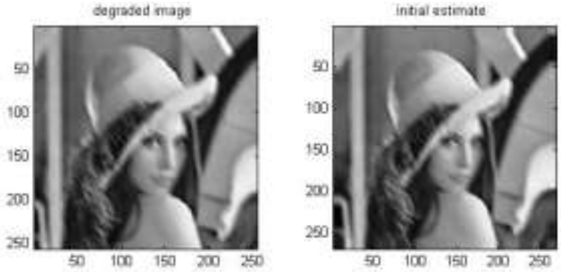


Fig 1 Ex:1::Degraded Stae and Initial Estimate

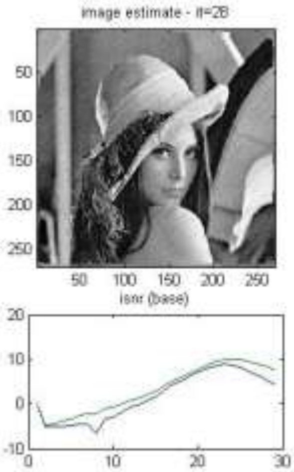


Fig 2 Estimate at Iteration=28

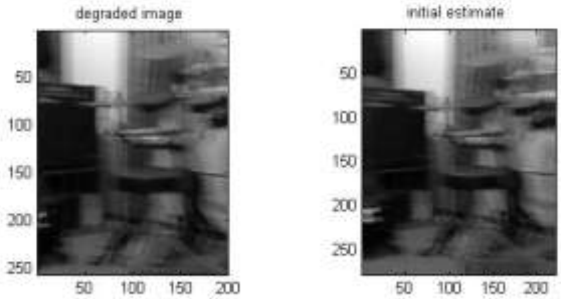


Fig 3 Ex: 2::Degraded Stae and Initial Estimate

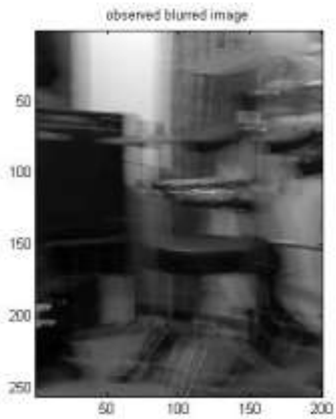


Fig 4 Observed Estimate

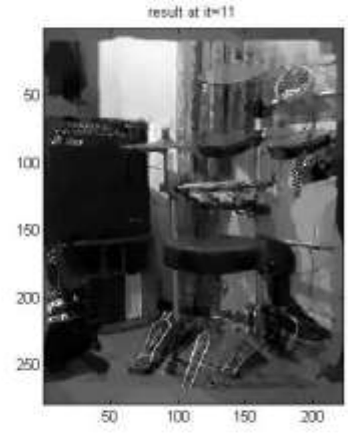


Fig 5 Estimate at Iteration=11

V. Conclusion

We have presented a method for removing defocus blur in images in the context of digitalrefocusing, 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 last image deconvolution method for efficient deblurring, a local blur estimation methodwhich 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. Screen image deconvolution 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, SID 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 SID, 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 SID, direct minimization of the cost functions typically used for deconvolution may not yield the desired sharp image estimates.

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