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Fast Blur Removal via Optical Computing

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ABSTRACT

Non-uniform image blur caused by camera shake or lens aberration is a common degradation in practical capture. Different from the uniform blur, non-uniform one is hard to deal with for its extremely high computation complexity as the blur model computation cannot be accelerated by Fast Fourier Transform (FFT). We propose to compute the most computational consuming operation, i.e. blur model calculation, by an optical computing system to realize fast and accurate non-uniform image deblur. A prototype system composed by a projector-camera system as well as a high dimensional motion platform (for motion blur) or original camera lens (for optics aberrations) is implemented. Our method is applied on a series of experiments, either on synthetic or real captured images, to verify its effectiveness and efficient.

Keywords: non-uniform blur; camera shake; lens aberration; optical computing;

1. INTRODUCTION

Image blur caused by camera shake and lens aberrations are both spatially varying and their removal mathematically can be implemented by non-uniform deconvolution. However, there are no accurate acceleration methods for non-uniform debblurring so far and thus researches in these two tasks largely suffer from the high computational cost. Here, we proposed to address the efficiency problem in these two tasks by optical computing.

The earlier works [1, 2, 3, 4, 5, 6] in optical computing basically focused on general purpose computing, such as matrix multiplication, Fourier transformation, matrix decomposition, etc. However, with the rapid development of digital computer, the advantages of optical computing in aspect of speed are greatly weakened. However, it is still promising to design specific optical computing systems for concrete tasks, which need intensive non-general calculations without acceleration implementations. For example, O'Toole et al. [7] use a projector-camera system to perform light transport computing, Lefebvreet al. [8] and Yu et al. [9] apply optical computing for pattern recognition.

To develop an optical computing system for fast non-uniform deblurring, we analyze the efficiency bottleneck of the non-uniform deblurring algorithms in camera shake removal and lens aberration compensation, and map the most time consuming modules to a physical process that can be implemented fast by an off-the-shelf imaging system. Then, the imaging module is incorporated into a deblurring framework and forms an efficient deblurring approach.

2. CAMERA SHAKE REMOVAL

Perspective geometry tells that camera shake blur may be intensively varying in spatial domain. However, due to the high complexity and computational cost of non-uniform blurring models, for a long time studies on camera shake removal formulate camera shake blur with uniform convolution and propose many deblurring methods[10, 11, 12, 13, 14]. With the progress of image deblurring, researchers refocus their attentions on non-uniform blur model. However, non-uniformity requires to compute convolution in pixel-wise manner and pursue optimum blur kernel by exhaustive searching, so the approaches [15, 16, 17, 18] all suffer from the high computational cost. Although patch-wise based deblurring [19] can be used to solve the non-uniform deblurring problem efficiently, the approximation accuracy is limited for the intensively varying blurry cases. To address the efficiency in non-uniform camera shake blur while keeping high computation accuracy, we resort to task specific optical computing.

Intuitively, the time-consuming pixel wise convolution corresponds to a spatially varying image blur process. This motivates us to build a new imaging system to physically simulate an imaging process (as shown in Fig. 1) that corresponds to the convolution exactly, and thus alleviate the computing process. In other words, we simulate the non-uniform computation directly instead of computing it pixel by pixel or approximating by patch-based methods.

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Specifically, we project the sharp image onto a planar screen as a synthetic scene and simulate the blurring process by imaging the screen using a shaken camera driven by a programmable motion platform.

For validation, we incorporate our high dimensional motion platform projector-camera system into non-uniform version of Richardson-Lucy deblurring algorithm. Neglecting the mechanical limitation of the system, it only takes a little longer than 1/15 second for an iteration using a 30fps digital camera (two snapshots in each iteration). In comparison, the pixel-based methods are orders of magnitude slower than our system, especially for large image sizes, while patch based methods are of much lower accuracy in cases of abruptly changing blur kernels. Fig. 1(a)(e) show the blurry image and true sharp image respectively. The estimated sharp images and residual maps at iteration 1, 10, 20 are shown sequentially in Fig. 1(b-d) and (f-h). The increasing sharpness and decreasing residue both validate that our system can be incorporated into deblurring framework easily to raise the efficiency without introducing large artifacts.

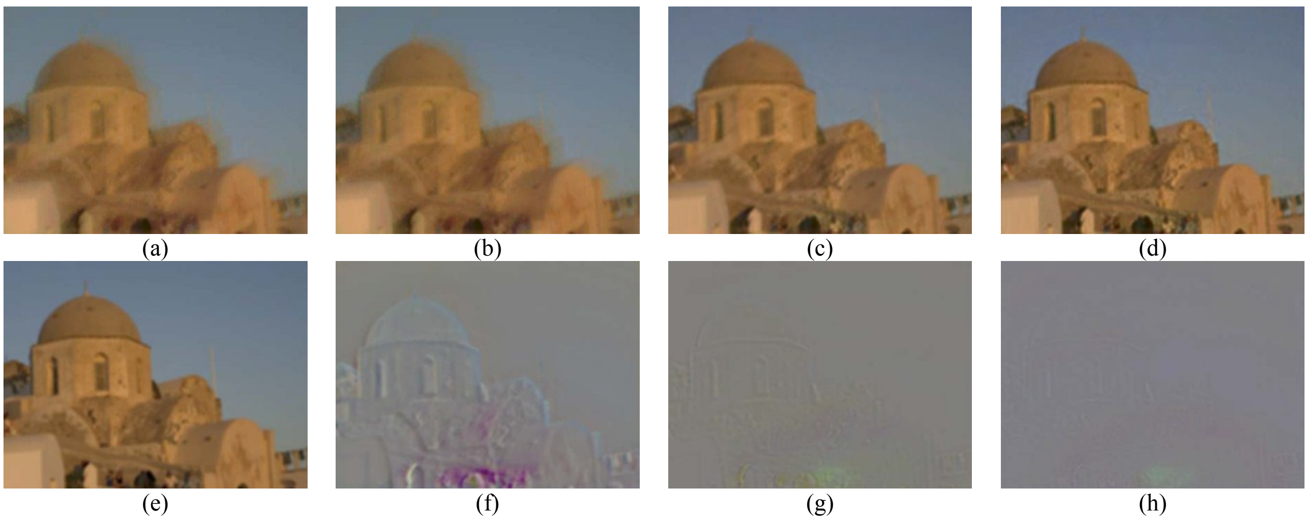

Figure 1. Result of fast non-blind deblurring with our optical computing system. (a) Blurry image (e) Sharp image. (b)(c)(d) Estimated sharp image at 1st, 10th and 20th iteration. (f)(g)(h) The residual error map of (b)(c)(d) with respect to (a).

3. LENS ABBERATION COMPENSATION

Optical aberration exists widely in daily photography and scientific imaging, and can degrade image quality significantly. To obtain high-quality images, one can resort to either adaptive optics [20, 21, 22 23, 24] during acquisition or computational restoration [25, 26, 27] after data capture. The latter is widely used because it is less expertise demanding and the required materials are of wider availability.

Whether adopting adaptive-optics-based or post-processing methods, we need the characteristic data of the lens's aberration, i.e. the point spread functions (PSFs), beforehand. To derive the aberration information, researchers have proposed several kinds of methods, e.g. phase diversity retrieval [28, 29] and calibration [25, 27, 30, 31]. All these methods require a complex procedure or some special devices. In sum, accurately obtaining the PSF of the lens is of vital importance but quite challenging.

Given the aberration data, one can use non-blind deconvolution to restore the latent image from a low-quality source. Firstly, the deconvolution needs to fit the convolution degeneration model iteratively to search for an optimal solution. Since lens aberration is often complex and spatially varying, the convolution must be conducted pixel-wise and is quite time consuming. Still, the high complexity and non-uniformity of lens PSFs make deconvolution extremely time-consuming.

With the aim of improving the image quality of low-end lenses simply and effectively, we propose a novel "touch-up" approach to address lens aberration via optical computing. Under the general framework of deconvolution, we use a display–camera system to perform calculations optically, as shown in Fig. 2(a). The convolution, with estimated PSF included in its algorithm, is conducted by capturing a displayed image using the original lens, and thus the deconvolution steps are implemented by performing a series of display–capture procedures. On one hand, the pixel-wise convolution can be computed by a display-capture and is thus quite efficient. On the other hand, the display–capture operation accurately simulates the degeneration model and eliminates the effects of PSF estimation error, so the proposed system achieves satisfactory performance, as shown in Fig. 2(b) and Fig. 2(c). Besides, the necessary devices of the proposed system are widely accessible and all the system calibrations and computing process are automatic, so our approach is easily implemented and offers a user-friendly interface.

(a) (b) (c)

Fig. 2. Prototype and results for image enhancement. (a) The setup. (b) Low-quality input image. (c) Aberration-compensated result.

4. SUMMARY AND DISCUSSIONS

To address the high computation cost of non-uniform deblurring, we propose to developing optical computing systems for face calculation. Benefited from the fast light transport and the parallelism of imaging system, optical computing systems can do specific operations very fast. Specifically to our systems, each CCD unit acts as an individual computing unit and each snapshot can achieve parallel processing of Mega- or even Giga- pixels, thus the proposed optical computing system provides a feasible and promising solution to fast non-uniform motion delburring.

So far, the proposed system is limited to non-blind deblurring and is somewhat limited in real applications. We also have done some extensions for blind camera shake removal via optical computing and gotten promising results [XXX]. The implementations for blind lens aberration compensation is one of our future work.

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