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Disparity-based space-variant image deblurring

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ABSTRACT

Obtaining a good-quality image requires exposure to light for an appropriate amount of time. If there is camera or object motion during the exposure time, the image is blurred. To remove the blur, some recent image deblurring methods effectively estimate a point spread function (PSF) by acquiring a noisy image additionally, and restore a clear latent image with the PSF. Since the groundtruth PSF varies with the location, a blockwise approach for PSF estimation has been proposed. However, the block to estimate a PSF is a straightly demarcated rectangle which is generally different from the shape of an actual region where the PSF can be properly assumed constant. We utilize the fact that a PSF is substantially related to the local disparity between two views. This paper presents a disparity-based method of space-variant image deblurring which employs disparity information in image segmentation, and estimates a PSF, and restores a latent image for each region. The segmentation method firstly over-segments a blurred image into sufficiently many regions based on color, and then merges adjacent regions with similar disparities. Experimental results show the effectiveness of the proposed method.

1. Introduction

Imaging a scene from a fixed camera viewpoint is generally required to capture a clear image. However, a camera often moves with respect to the target scene during a single exposure time. This is mostly the way: without using a tripod, taking a picture is frequently affected by a hand tremor. A camera image is obtained as the integration of the input intensity of electromagnetic radiation for an exposure time. The motion of the camera during the exposure time makes *motion blur* in the image. Under a poor lighting environment, a camera image is typically captured by a long exposure time, and a hand tremor is likely to cause a serious sequential rigid motion of the sensor array, resulting in a highly motion-blurred image. In many applications, motion blur is undesirable, and researchers have investigated methods of *deblurring* which restore a clear *latent image* from a *blurred image*. Deblurring algorithms mostly consists of two main steps, (a) estimation of a blur kernel, namely, *point spread function* (PSF) corresponding to the camera or object motion, and (b) latent image reconstruction based on the estimated PSF.

Many deblurring algorithms [1,2] take a single blurred image as the input, and they generally has two major disadvantages, longer computational times and lower accuracies compared to multi-image-based algorithms, due to the deficiency of information. Recently the advances in CMOS sensors have made possible rapid capture of images, and multi-image-based deblurring [3–9] has become more feasible.

The hybrid imaging method [8] measures the camera motion from a sequence of images, and uses the motion to compute a PSF. However, using special hardware is the major disadvantage of the method. Double-image-based approaches have been proposed, and many of them

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employ a short-exposure (dark or noisy) image in addition to a blurred image [3–7]. Jia et al. used an under-exposed (dark) image and a blurred image to produce an optimal color mapping function [6]. Without PSF estimation, a high-quality image is obtained by the color mapping function. However, the dark images they used were not noisy. Other important methods using a short-exposure image estimate a PSF mostly using a *noisy image*, and restore a latent image with the PSF [3–5,7]. Actually, their work can be considered as either deblurring of a blurred image using a noisy image or denoising of the noisy image using the blurred image. The (blurred or noisy) images of different exposure times and possibly different ISOs can be subsequently captured in the exposure bracketing mode of a camera,[1] prohibiting serious geometric transformation between any pair of images [3].

Most of existing methods assume two kinds of blur models. One is the space-invariant model in which the PSF is identical for a whole image, and the other is the space-variant model in which the PSF can vary with the location. Since an object scene generally has its spatial variation of the distance from the sensor array, the motion of features in a camera image varies with the spatial location, and space-invariant models cannot handle the spatial differences of the blur.[2] Šorel and Flusser [9] considered blur in the pinhole camera model depending on the depth of scene and the camera motion, and estimated a depth-dependent (space-variant) PSF for a piecewise planar scene from multiple blurred images. However, the method requires specification of a region of approximately constant depth as a user input, and the camera motion is assumed to be an arbitrary curve parallel to the image plane without any rotations. To deal with general camera motion, a blockwise approach for PSF estimation has been proposed [4]. However, the block to estimate PSF is a straightly demarcated rectangle which is different from the shape of an actual region where the PSF can be properly assumed constant. In case there exists significant spatial variation of the groundtruth PSF in a block, the blockwise PSF still cannot reliably handle the spatial variation. If a sufficiently small block size is chosen to properly resolve the spatial variation, features such as edges and corners in each block will be reduced, and PSFs will not be reliably estimated for many blocks.

A latent image is estimated by deconvolution of a blurred image with a PSF. For the image restoration, methods based on total variation (TV) have been often used [11,4]. The TV-based methods have some advantages in that they finds a better optimized solution compared to the Richardson–Lucy (RL) algorithm [12] (which is employed in [3]), and they generally suppress the noise and sharpen edges. Unfortunately, the objective function of the TV-based methods has an L_1 regularization term, and the solution cannot be generally expressed in a closed form. While the space-domain iterative method based on conjugate gradient (CG) [13] does not usually converge rapidly, the half-quadratic iterative approach based on hyper-Laplacian distribution priors [14] is very efficient by using the fast Fourier transform (FFT).

Disparity[3] (or binocular disparity) is the locational difference of a scene point in the images from two distinct viewpoints, and is one of the most important depth cues in human and machine vision. *Motion parallax* is the parallax achieved by motion of a viewpoint, and can be equivalently interpreted as disparity. In general, the magnitude of motion parallax is proportional to the amount of motion of the viewpoint and the inverse of the depth (the distance between the viewpoint and object). Similarly, the magnitude of disparity is proportional to the distance between the two viewpoints and the inverse of the depth (the distance between the viewpoints and object). The motion-blurred image can be represented as the temporal integral of a latent image with time-varying motion parallax. That is, the blur kernel corresponds to the temporal integral of a neutral scene point with the time-varying motion parallax. In case of deblurring using at least two images, we can estimate the disparity between any pair of images, and the disparity can be considered as a discrete version of the time-varying motion parallax, and therefore we assume regions of similar disparities are likely to have similar blur kernels.

In this paper, we propose a disparity-based regional PSF estimation and restoration algorithm (see Fig. 1). It uses a pair of images from an object scene: a blurred image captured with long exposure and possibly low ISO, and a noisy image with short exposure and possibly high ISO. We assume there is disparity between the two images caused by camera motion which also causes the blur of the blurred image. Therefore, we utilize the fact that a PSF is substantially related to the local disparity between two views: a pair of blurred and noisy images. We first over-segment the blurred image into regions based on color (RGB intensities) using the graph-cut method [15–18]. Then, we detect corners of the blurred image with the Harris detector [19], and estimate the disparities of the corners between the two images by the subpixel hierarchical block matching [20–24]. The disparity of each segmented region is determined as the vector median[4] of the disparities of the corners in the segmented region. Finally, if adjacent regions have similar disparities, they are merged into one region. Meanwhile the homography between the two images is estimated from the block matching result, and the noisy image is registered to the blurred image according to the homography.[5] Now a PSF

[1] Some non-SLR compact digital cameras as well as many DSLR cameras have an exposure bracketing function.

[2] Actually, an important portion of the PSF is produced by many factors that are independent of the relative motion between the scene and sensor [10], such as defocus, diffraction, spherical and chromatic aberrations, and wave aberrations. Those factors are mainly characterized by the geometry of the aperture, lens, and mirror in the imaging system. The total PSF caused by motion as well as those factors, is spatially variant in general. This paper discusses on the space-variant total PSF.

[3] In this paper, we consider disparity basically as two-dimensional vector(s).

[4] The vector median is defined in Section 3.

[5] Homography is suitable not for a general 3D scene, but for a planar scene. However, as demonstrated earlier, a pair of blurred and noisy images we use for deblurring, are captured intentionally without serious geometric transformation between the pair. Therefore, a singe homography matrix is a