Proposal: Blind Image Debluring for Camera Shake Blur

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1 Background

Image restoration palys an critical role in modern imaging systems, which aims to provide high-quality images under complex environments such as motion, undesirable lighting conditions, and imperfect system components. Image debluring has attached great attention in recent years. Specificly, this problem can be divided into blind image debluring and non-blind image debluring, the non-blind ones aim to infer a latent sharp image from one or several blurry images, while the blind techniques are also required to derive an accurate blur kernel. Existing approaches can be grouped into five categories: Bayesian inference framwork, variational methods, sparse representation-based methods, homography-based modeling, and region-based methods. This project proposes a blind debluring method to reconstruct blurry image with camera shake blur.

2 Objectives

First, the blur kernel is estimated from the input image. The estimation process is at an acceptable speed.
Second, using the estimated kernel, we apply a standard deconvolution algorithm to estimate the latent (unblurred) image.

3 Methods

Our algorithm takes as input a blurred input image B, which is assumed to have been generated by convolution of a blur kernel K with a latent image L plus noise:

$$\mathbf{B} = \mathbf{K} * \mathbf{L} + \mathbf{N}, \tag{1}$$

where $\mathbf{N}$ is Gaussian with variance σ^2.
And we assume that all image blur can be described as a single convolution; there is no significant parallax, any image-plane rotation of the camera is small, and no parts of the scene are moving relative to one another during the exposure. Our approach currently requires a small amount of user input.

In order to estimate the latent image from such limited measurements, it is essential to have some priori knowledges about image **L** and blur kernel **K**. Fortunately, some research in natural image statistics have shown that, images of real-world scenes subject to heavy-tailed distributions in their gradients. The kernels are positive and sparse.

Algorithm 1 Deblur

STEP1 Pre-processing:

(**a**) compute the gradients magnitudes of the input blurry image

(**b**) get the histogram of the image gradients, which is a heavy-tailed distribution

(**c**) use the mixture model of Gaussians to approximate the disturibution of the image gradients

STEP2 Kernel estimation

(**a**) initialize kernel size

(**b**) conjugate gradient descent on Maximum a-Posteriori(MAP) solution

(**c**) use a sharpen-edge-based method to strengthen details

(**d**) find the optimal kernel size and window size.

STEP3 Image reconstruction

To recover the deblurred image given this estimate of the kernel, we will experiment with a variety of deconvolution methods, including those of Geman [1992], Neelamani [2004] , van Cittert [Zarowin 1994] and Poisson image reconstruction [Weiss 2001], then to discuss which method can get the best performance.