Signal Processing 103 (2014) 399–414

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

A novel gradient attenuation Richardson–Lucy algorithm for image motion deblurring

Hao-Liang Yang, Po-Hao Huang, Shang-Hong Lai *

Department of Computer Science, National Tsing Hua University, Hsinchu 300, Taiwan

A R T I C L E I N F O

Article history:
Received 2 July 2013
Received in revised form
12 January 2014
Accepted 20 January 2014
Available online 3 February 2014

Keywords:
Blur kernel estimation
Richardson–Lucy algorithm
Image deblurring
Motion blur
Blind image deconvolution
Image restoration

A B S T R A C T

This paper presents a novel blind image deconvolution algorithm for motion deblurring from a single blurred image. We propose a unified framework for both blur kernel estimation and non-blind image deconvolution by using bilateral filtering (BF) and a new image deconvolution algorithm, called the Gradient Attenuation Richardson–Lucy (GARL) algorithm. In the blur kernel estimation stage, we show that an initial blur kernel, which is used for starting an alternating kernel refinement process, can be obtained from the blurred image with a quadratic regularization approach. In the non-blind image deconvolution stage, we exploit the image gradients and develop the GARL algorithm to alleviate the notorious ringing problem in the Richardson–Lucy-based image restoration approach. Furthermore, the loss of image details due to the suppression of the ringing artifacts around the regions with strong edges is recovered with an incremental detail recovery procedure. The proposed framework is simple yet effective compared to previous statistical approaches. Experimental results on various real data sets are given to demonstrate superior performance of the proposed algorithm over the previous methods.

1. Introduction

Motion blur is caused by relative motion between the camera and the scene within the exposure time period. Restoring motion blurred images is a long-standing research problem in computer vision and image processing. Various algorithms have been proposed to tackle this problem and they can be roughly categorized into three groups: deblurring from a single image [8,10,12,14,18,19,21,23,24,26], deblurring from multiple images [6,7,13,15,20,22,25], and computational photography [9,27].

The real camera motion is usually too complicated to estimate from a blurred image when it involves camera rotation or large scene depth variations. To simplify the problem formulation, previous researches usually assumed the camera motion is perpendicular to the optical axes and the effect of scene depth variation can be neglected. In other words, the blur kernel, or named point spread function (PSF), is assumed to be spatially invariant. Under this assumption, a blurred image, B, can be modeled as the convolution of the clear image I, which is the goal of the image restoration, and the blur kernel F:

$$B = I \otimes F + N \tag{1}$$

where N is an additive noise image, and $\otimes$ is the convolution operator. This problem is called blind deconvolution if both I and F are unknown, or non-blind deconvolution if only I is unknown [3].

In this paper, we propose a unified framework to resolve the problem of motion deblurring from a single image under the assumption of spatially-invariant kernel. The proposed framework is based on introducing the concept of gradient attenuation [5] into the Richardson–Lucy (RL) algorithm [1,2] for both blur kernel estimation

* Corresponding author. Tel.: +886 3 5742958; fax: +886 3 5731201.
E-mail address: lai@cs.nthu.edu.tw (S.-H. Lai).

http://dx.doi.org/10.1016/j.sigpro.2014.01.023
0165-1684

and non-blind image restoration. For an input blurred image, we first construct a pyramid representation of this image and estimate the blur kernel in a coarse-to-fine manner. The estimated blur kernel is also represented as a pyramid representation and further used for non-blind deconvolution to restore a ringing-suppressed image. For the non-blind deconvolution, we propose a gradient-attenuated Richardson–Lucy (GARL) algorithm that alleviates the ringing artifact in the RL algorithm and the computation is accomplished efficiently. The flowchart of the proposed motion deblurring framework is illustrated in Fig. 1.

The contributions of this paper are listed as follows:

- We propose an initial blur kernel obtained from the blurred image with a quadratic regularization approach for starting an alternating kernel estimation process (Initial PSF estimation).
- We exploit the gradient attenuation concept and modify the standard RL algorithm for suppressing ringing artifacts in the RL-based image deconvolution (GARL algorithm).
- We propose an iterative details recovery procedure that can recover missing details due to ringing suppression (Details recovery).
- We combine GARL and bilateral filtering (BF) [4] algorithms for both blur kernel estimation and non-blind deconvolution in a unified framework.

The rest of this paper is organized as follows: The remaining of Section 1 describes the related works. Non-blind deconvolution and blur kernel estimation algorithms are proposed in Sections 2 and 3, respectively. Experimental results are reported in Section 4. Finally, we conclude in Section 5.

1.1. Related work

1.1.1. Blur kernel estimation

The blind image restoration problem in (1) is ill-posed because I and F are highly under-constrained and there are infinitely many possible combinations of I and F such that their convolution is equal to the blurred image B. Previous works typically assumed that the blur kernel has a simple parametric form (e.g., single one-directional motion or a Gaussian model). However, as Fergus et al. showed in [8], the blur kernels are usually too complicated to be represented with simple parametric forms. They hereby proposed to utilize ensemble learning to estimate the blur kernel with a sophisticated variational Bayes inference algorithm, which employs the property of specific distributions of image gradients for natural images to approximate the posterior distribution. Levin [10] also exploited image statistics for estimating blur kernels. Nevertheless, the motion blur is assumed to be unidirectional with constant velocity. Jia [12] estimated the blur kernel by using the transparency information of blurred region. The limitation of this method is the need to find regions that can produce high-quality matting results. Dai and Wu [21] also made use of the matting results and proposed an alpha-motion blur constraint model which provides local linear constraint for the blur parameters. Shan et al. [18] proposed two probabilistic models to improve image restoration. One is to model the spatially random distribution of noise, and the other is a smoothness prior model which can reduce the ringing artifacts. Joshi et al. [19] utilized pairs of predicted sharp edge and blurred edge to estimate the blur kernel based on the assumption of blurred step edges such that the suitable kernel is of a small size and described with a single peak. Cai et al. [23] proposed to maximize the sparsity property of motion blur kernel in a curvelet system, which can provide a good constraint on the curve-like geometrical support of motion blur kernel. However, the real blur kernels are often too complicated for this curvelet representation. Levin et al. [24] discussed the limitation of the maximum a posterior (MAP) approach and suggested to estimate the MAP of F alone (marginalizing over I). However, the computational aspects are challenging. Cho and Lee [26] proposed a latent image prediction step, which applied shock filter to recover the sharp edge information for estimating the blur kernel. This gradient prediction step can remove small

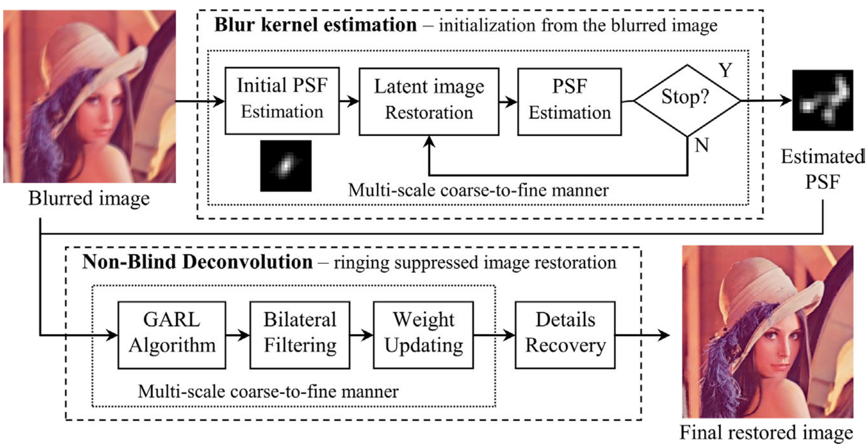

Fig. 1. Flowchart of the proposed framework of our blind image deconvolution algorithm.