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Bayesian non-parametric gradient histogram estimation for texture-enhanced image deblurring

Chunwei Song [a], Hong Deng [b], Huijun Gao [a,*], Hongzhi Zhang [b], Wangmeng Zuo [b]

[a] School of Astronautics, Harbin Institute of Technology, 92, West Dazhi Street, 150001 Harbin, China
[b] School of Computer Science and Technology, Harbin Institute of Technology, 92, West Dazhi Street, 150001 Harbin, China

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ABSTRACT

Image deblurring aims to restore the latent clean image with textures and details from the blurry observation, and is a classical yet active inverse problem in image processing and low level vision. Even though various methods based on image priors have been proposed, the deblurring results by the existing methods usually tend to be over-smoothed and cannot recover fine scale textures. On the other hand, gradient histogram prior has been introduced for texture-enhanced image denoising but the gradient histogram estimation model cannot be used to estimate reference histogram from blurry image. In this paper, we first suggest a gradient histogram preserving (GHP) based image deblurring method, where the reference histogram is parameterized by Hyper-Laplacian distribution. Considering the complexity of blurring process, a Bayesian non-parametric method, Gaussian Processes regression, is utilized for estimating histogram parameters. The experiments demonstrate that, the histogram parameter estimation method is effective, and the proposed GHP based image deblurring method can well restore image textures and improve image quality.

1. Introduction

Image blurring is a long standing problem in computer vision and computational photography, which is even more common nowadays with the resolution of cameras getting higher and higher. Usually, blurry image $\mathbf{y}$ can be modelled as the linear convolution between clean image $\mathbf{x}$ and convolution shift-invariant kernel $\mathbf{k}$ with additive sensor noise ϵ, that is, $\mathbf{y}=\mathbf{k}*\mathbf{x}+\epsilon$, where $*$ denotes the 2D convolution operator. If we assume the kernel $\mathbf{k}$ to be known, to restore the clean image falls into the problem of non-blind image deblurring or deconvolution, which is typically under-constrained. To solve this problem, the maximum a posterior (MAP) model is widely used, which is also used in some other field such as power grid control [1–4] and networked control systems [5], and contains two terms: the fidelity term (or likelihood) and regularization term (or prior). When independently and identically distributed (i.i.d.) Gaussian noise is assumed, the fidelity term takes the quadratic form with the coefficient matrix to be identity. In that situation, the non-blind image deblurring MAP model can be written as follows:

$$\arg\min_{\mathbf{x}} \|\mathbf{y}-\mathbf{k}*\mathbf{x}\|_2^2+R(\mathbf{x}). \tag{1}$$

where $R(\cdot)$ represents the regularization term that imposes constraint on the estimated image $\mathbf{x}$. Since the fidelity term cannot uniquely determine the clean image $\mathbf{x}$ out of the degenerated image $\mathbf{y}$, the regularization term is especially important for the purpose of image restoration, which is also what we care about mostly.

Image regularization or prior model has been widely discussed, especially with the progress on sparse coding models and algorithms. Roughly speaking, regularization models in image processing and restoration fall into several categories [6]: filter-bank-based, patch-based, gradient-based, etc. Filter-bank-based regularization [7,8] aims to formulating the response of a set of filters, a typical method like Field of Experts [7], where the filters (or potential function in MRF) are learned from examples. Patch-based priors are not unfamiliar, as sparse representation methods are quite popular in the past a few years, such as in [9–13], just to name a few. Gradient-based regularization models are quite common especially for image deblurring, since image gradient or edges contribute to image restoration and kernel estimation (in blind deblurring), as described in [14–19], which can effectively avoid trivial solutions.

Gradient-based model is characterized based on the fact that image gradient is quite sparse and follows the heavy-tailed

* Corresponding author.
E-mail addresses: wolvesandme@gmail.com (C. Song), cshdeng@163.com (H. Deng), hjgao@hit.edu.cn (H. Gao), zhanghz0451@gmail.com (H. Zhang), cswmzuo@gmail.com (W. Zuo).

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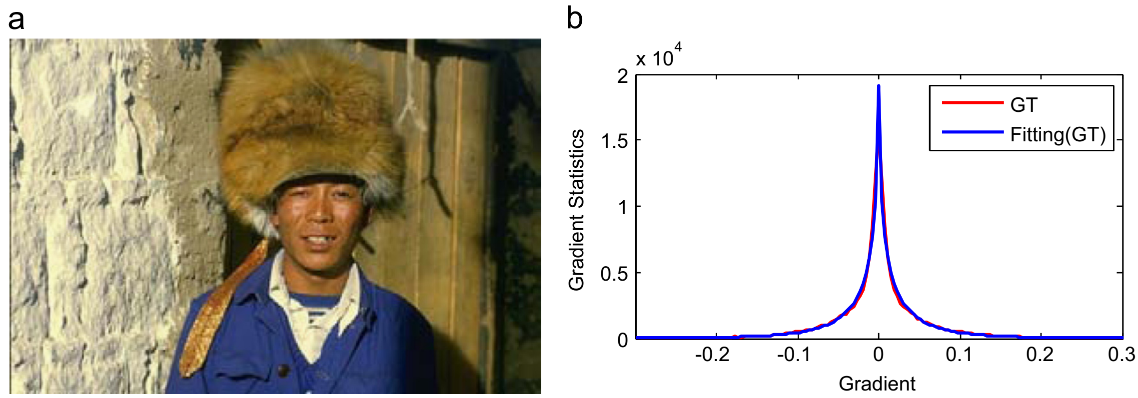

Fig. 1. Image gradient histogram approximation. (a) Clean image. (b) Gradient histogram statistics, with parameters $\alpha = 0.5893$, $\rho = 0.5700$ (readers can refer to Eq. (2) for more information about these two parameters). "GT" stands for ground truth histogram, and "Fitting (GT)" is the parametric histogram of "GT". They are defined in Section 2.1.

distributions. A common model to describe this property is Laplacian distribution, and the corresponding regularization term can be roughly written as $\|\nabla \mathbf{x}\|_1$ with logarithm operation and constants omitted, where ∇ represents gradient operator. Although Laplacian distribution has the property of heavy-tail, it is not quite suitable for real-world image representation, whose distribution is much more heavier. In [20], a Hyper-Laplacian prior is applied to model the heavy tail property, which has better ability to characterize real-world image. Actually, as shown in Fig. 1, Hyper-Laplacian distribution is a great approximation to empirical gradient distribution. Meanwhile, histogram as a global feature descriptor of image has been extensively utilized in texture representation and classification [21,22], and recently, been successfully employed in image denoising [23–25]. Therefore, a histogram-based gradient prior model for image non-blind deblurring is considered.

Although Hyper-Laplacian distribution can better describe image distribution, images of different types have different distribution parameters, as shown in [26]. Of course, it should make more sense if the Hyper-Laplacian prior parameters can adaptively change with the image under processed, while many models commonly adopt constant parameters for ease of computation as in [27], which is not quite reasonable. Therefore, a robust prior parameter estimation method is demanding to better improve image restoration.

In this paper, Gaussian Processes regression is implemented to estimate Hyper-Laplacian distribution parameters, which is also implemented in some other field, such as networked control [28–30], fuzzy systems [31,32] and fault detection [49]. Considering the successful utilization of gradient histogram preserving in image restoration [23–25], a histogram matching constraint is introduced to improve image deblurring results. Compared to other similar Hyper-Laplacian distribution parameter estimation methods like [26], our method is more effective and the estimated parameters are used not only for gradient regularization, but also for explicit utilization of gradient statistics for texture-enhanced deblurring. It is also worth noting that Mei et al. [25] also utilized similar schemes for image deblurring, but the estimation process of the reference histogram is rather heuristic and the results were not quite of high accuracy. Indeed, the experiments show that our Gaussian Processes regression based method leads to better parameter estimation, and the proposed model has better performance than pure gradient regularization method from the perspective of both quantitative metrics and visual quality (refer to Fig. 2 for an example).

2. Problem formulation

In this section, we will first present the gradient histogram preservation (GHP) based non-blind deblurring model. To better implement this method, a Gaussian process regression based reference gradient histogram estimation method is proposed. Based on the estimation accuracy analysis, one will find that the proposed method is accurate enough for image deblurring problems. Before we proceed to the details, some notations will be given first for later use.

2.1. Main notation

In this work, we denote matrices by capital letters (X), vectors as bold, lower case letters ($\mathbf{x}$), scalar as lower case letters (y), and probability distribution parameters as lower case Greek letters (α). Three kinds of histograms are involved in this paper. The clean image gradient histogram is denoted as ground truth or "GT" in legends. Fitting Hyper-Laplacian distribution to ground truth histogram using some Hyper-Laplacian fitting methods as discussed in [33,34], we can get the parametric histogram which is denoted as fitting histogram or "Fitting(GT)" in legends. By estimating the ground truth histogram from blurry image, we can get the estimated histogram which is named by "Est.(Blur)" in legends. Besides, some other notation that may not be consistent with that described here or not given here will be explained explicitly when used.

2.2. GHP based image deblurring model

Before we delve into the algorithm details, we first introduce the Hyper-Laplacian distribution, which can be parameterized as

$$p(x|\alpha,\rho) = \frac{\rho\alpha^{1/\rho}}{2\Gamma(1/\rho)}\exp(-\alpha|x|^{\rho}) \tag{2}$$

where α and ρ are the distribution parameters, and $\Gamma(\cdot)$ is the gamma function. Considering the fact that image gradient is usually centered at zero, the mean of the distribution in Eq. (2) is omitted. Noticeably, α represents the scale of distribution to some extent, while ρ depicts the distribution shape, which is normally less than 1 but greater than 0 for real-world image. But for the computation simplicity, special values like 2/3, 1/2 and 1 are set for ρ as in [27]. It is worth noting that $\rho < 0$ is allowable when it is used for the construction of shrinkage operation, and in that situation, an expansion rule is achieved as mentioned in [35].

In the following, we will introduce the main algorithm. Following the method in [23], the histogram matching method for