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Saturation-Value Blind Color Image Deblurring with Geometric Spatial-Feature Prior

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Abstract. Blind deblurring for color images has long been a challenging computer vision task. The intrinsic color structures within image channels have typically been disregarded in many excellent works. We investigate employing regularizations in the hue, saturation, and value (HSV) color space via the quaternion framework in order to better retain the internal relationship among the multiple channels and reduce color distortions and color artifacts. We observe that a geometric spatial-feature prior utilized in the intermediate latent image successfully enhances the kernel accuracy for the blind deblurring variational models, preserving the salient edges while decreasing the unfavorable structures. Motivated by this, we develop a saturation-value geometric spatial-feature prior in the HSV color space via the quaternion framework for blind color image deblurring, which facilitates blur kernel estimation. An alternating optimization strategy combined with a primal-dual projected gradient method can effectively solve this novel proposed model. Extensive experimental results show that our model outperforms state-of-the-art methods in blind color image deblurring by a wide margin, demonstrating the effectiveness of the proposed model.

AMS subject classifications: 65J22, 65K10, 65T50

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1 Introduction

Color image deconvolution is typically a fundamental preprocessing step in various image processing tasks and computer vision fields [3, 7, 49] such as image segmentation

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[19, 23, 71], object recognition [27], medical imaging [42, 58] and astronomical imaging [55]. Single image deblurring aims to recover a sharp image u from a single observed blurry and noisy image g with a known or unknown blur kernel K. Since camera shake is inevitable when using hand-held devices, the resulting motion blur is a common phenomenon in the taken photos. To remove the blur and recover the clear image, the degradation of the blurry image from the clear one is mathematically formulated as :

$$g = Ku + n, \tag{1.1}$$

where again K is the known or unknown blurring operator and n is some additive white Gaussian noise.

In most cases, the information acquired from a blurry image is the observed image itself. The task of recovering the sharp image can be further categorized into estimating both the blur kernel and the latent clear image (referred to as blind deblurring) and the deconvolution of the blurry image with the known kernel (referred to as non-blind deblurring). In general, blind image deblurring is much more challenging as both the blur kernel K and the latent clear image u in (1.1) need to be restored [1,8,18,35,38,47]. In the blind image deblurring process, two main method categories are always considered. The first one is to jointly estimate the blur kernel K and the sharp latent image u by model-based methods [8,53]. The second one is to first estimate the blur kernel and then obtain the final deblurred results using some outstanding non-blind deblurring approaches, including model-based methods [10,30,31,46,60,72], as well as some deep learning-based methods [43,69]. Since the blur kernel is critical for blind image deblurring, our proposed method will first estimate the blur kernel from the color degraded images and then use other non-blind methods to obtain the final results.

Due to the ill-posedness of the model (1.1), additional prior knowledge [36, 46, 47, 53, 56, 65, 66] should be considered on the latent sharp image and the estimated kernel to obtain a reasonable result. To regularize such ill-posed blind deblurring problems, statistical observations of blurry and clear images are crucial for designing an effective prior, which can help to produce a more accurate kernel and clear image. In Bayesian statistics, Levin *et al.* [34] assumed the sparsity of the image gradients within the maximum a posterior (MAP) estimation. This prior, however, assumed a uniform distribution for the blur kernel; otherwise, it could fail. Various natural image priors have been proposed to find a finer estimated kernel and a sharper intermediate latent image with salient edges. Chan and Wong [8] used TV regularization to generate a sparse gradient of the latent sharp image. To further facilitate the recovery of sharp edges, the L_0-regularized gradient sparsity prior was introduced by Xu *et al.* [62]. Pan *et al.* [46] proposed a blind deblurring method using extra L_0-regularized intensity sparsity for deblurring text images. Later, Pan *et al.* [47] further proposed a dark channel prior. The motivation for this dark channel prior came from the observation that the clear image is sparser than the blurry ones. Moreover, patch priors introduced by Sun *et al.* [56] and internal patch recurrence by Michaeli and Irani [41] have also attracted much attention in blind image deblurring. Besides, recovering the intermediate latent images with well-preserved edges and textures is also crucial