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Total variation based variational model for the uneven illumination correction

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ABSTRACT

It is well known that an image is the pixel-wise multiplication of two components (illumination and reflectance) that are described as intrinsic images. To enhance the visual quality of a degraded image with uneven illumination and low local contrast, it is an effective way to extract the illumination or reflectance from the image and correct the unevenness of illumination. In this paper, we propose a variational model to estimate the illumination and reflectance from the degraded image for the uneven illumination correction. The proposed model is solved by the alternating minimization scheme and the augmented Lagrange method. We give some theoretic analysis of our model and convergence analysis of the algorithm. Experimental results show that the proposed model can achieve excellent performance in the correction of the uneven illumination.

1. Introduction

An image can be viewed as the pixel-wise multiplication of two components (illumination and reflectance) that are described as intrinsic images in [1]. In a real scene, the illumination is usually uneven with a high dynamic range, which will result in low quality images. Thus image enhancement methods for the correction of uneven illumination are required to improve the visual quality of the degraded image.

There are a large number of image enhancement methods that have been proposed in the literature. A type of methods involve logarithmic transformations [2], powers-law transformations (gamma correction) [3], histogram equalization [4,5], histogram matching [6] and coherence-enhancing diffusion [7], among others.

Another category of methods are inspired by Retinex that is a model to explain how the human visual system (HVS) perceives colors under varying illumination conditions. These methods extract typically the illumination or reflectance from a degraded image and correct the unevenness of the illumination or simply extract the reflectance as the enhanced image. Thus, it is a crucial task to estimate the illumination or reflectance from the degraded image; however, this is an ill-posed inverse problem. Based on Retinex theory, many methods [8–24] have been proposed to cope with this problem.

Among the Retinex-inspired algorithms, the center/surround algorithms [8–12] are widely used, including the single-scale Retinex (SSR) [8], multi-scale Retinex (MSR) [9] and multiscale Retinex with color restoration (MSCR) [10]. These algorithms regard the smoothed version of the degraded image as the illumination component and improve the contrast through dividing the input image by the illumination. In PDE-based Retinex-inspired methods [13–15], the illumination is obtained by solving a partial differential equation (PDE). In [13,14], decomposition algorithms were developed based on the solution of Poisson equations, which can be solved efficiently and effectively by the fast Fourier transformation (FFT). The main assumption behind these algorithms is that the illumination varies smoothly, while the reflectance is piecewise constant where discontinuities correspond to the edges in the image. In [15], Liang et al. estimated the illumination component by iteratively solving a nonlinear diffusion equation. In [16], the guided filter was used to estimate the illumination of the input image. In [17], Smith et al. proposed an uneven illumination method for optical microscopy applications without the need of reference images. In [18], Peng et al. proposed a optical microscopy image correction method based on lowrank and sparse decomposition which can achieve high-accuracy with significantly fewer input images. In [19], based on the classic homomorphic filter, Shen et al. proposed an efficient thin cloud removal method for visible remote sensing

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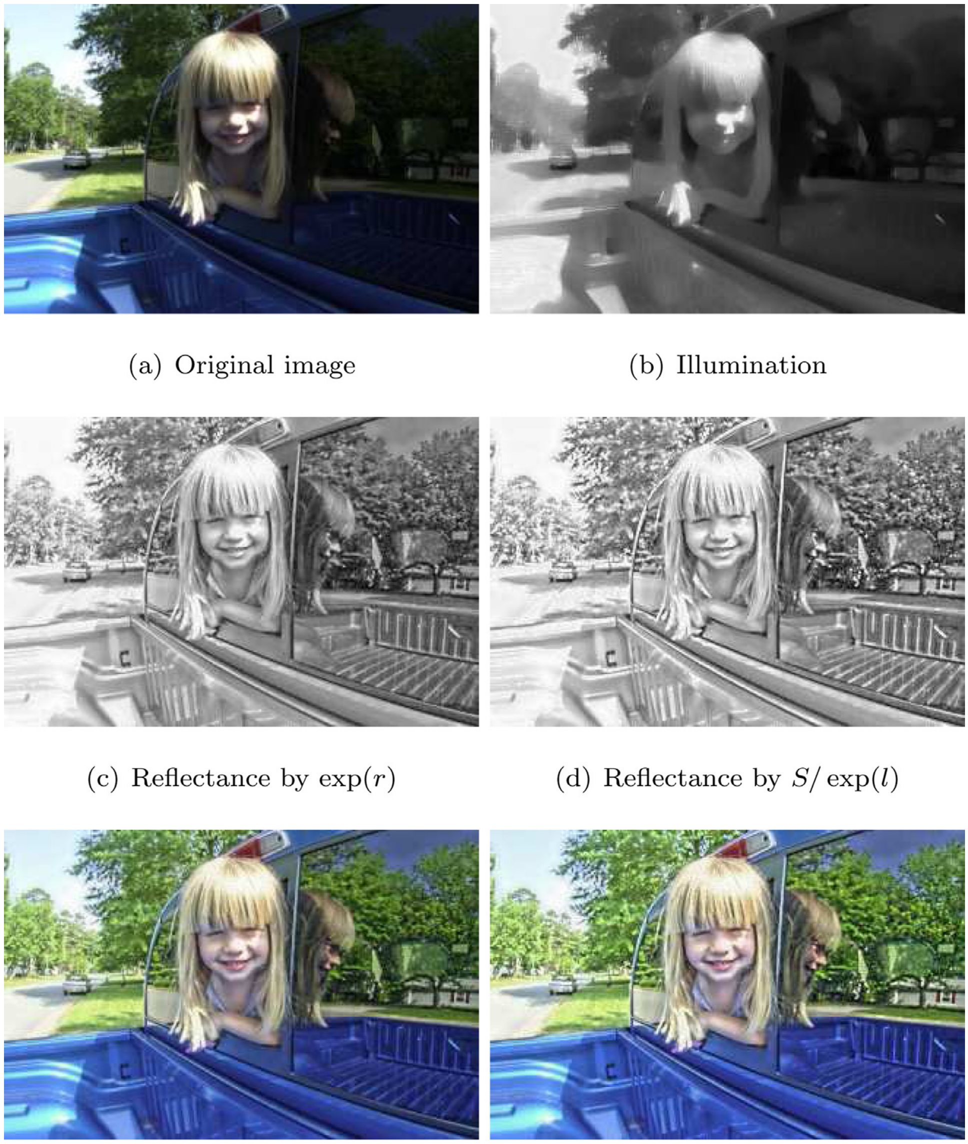

(a) Original image (b) Illumination

(c) Reflectance by $\exp(r)$ (d) Reflectance by $S/\exp(l)$

(e) Enhanced image by $\exp(r)$ (f) Enhanced image by $S/\exp(l)$

Fig. 1. The illumination, reflectance and enhanced images of our model.

images. In [20], Li et al. proposed a shadow removal method for aerial images, which uses the nonlocal operator to regularize the shadow scale and the updated shadow-free image.

Another type of Retinex-inspired methods is based on the variational framework [18–24]. These algorithms are implemented by solving a constrained optimization problem under the hypothesis that both the reflectance and illumination are spatially smooth. The difference of these methods mainly involves dissimilar norms for the regularization terms and diverse constraints. In [21], Kimmel et al. first proposed a variational model, in which the L^2-norm is used for regularizing both the illumination and reflectance. They used a projected normalized steepest descent (PNSD) method to solve the model, while the constraint was guaranteed by the projection $l = \max(l, s)$ where l and s are the illumination and the initial image in the logarithmic domain, respectively. In [22], Ng and Wang proposed a variational model with the TV (total variation) regularization on the reflectance. They divided the minimization problem into two subproblems by the alternating minimization scheme and utilized the split Bregman method to solve both subproblems. In addition, a projection step is also needed to ensure the constraints during the iterative process. In [23] and [24], two perceptually inspired variational models were proposed, in which the L^p-norm for regularization of reflectance was adaptively chosen. In [25], Jingwei and Xiaoqun proposed a higher order TV model, which was solved by the primal-dual splitting algorithm. To make the solution satisfy the constraints, the projection about illumination and reflectance was done during the iterative process. In [26], Wang and He proposed a variational model with barrier functional and solved the model by the steepest decent and semi-implicit finite difference. In [27], Fu et al. proposed a probabilistic variational model, which is based on a simultaneous estimation of the illumination and reflectance in the linear domain instead of the logarithmic domain.

In this paper, we propose a new variational TV-based model to correct the uneven illumination of the degraded image. The numerical solution of our model is proved to satisfy the constraints and so the projection step is not needed during the iterative process. Next, an alternating minimization scheme and the augmented

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