A HYBRID $L_2 - L_p$ VARIATIONAL MODEL FOR SINGLE LOW-LIGHT IMAGE ENHANCEMENT WITH BRIGHT CHANNEL PRIOR

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INTRODUCTION

In this paper, we consider and study the norm variable and propose a hybrid $L_2 - L_p$ variational model with bright channel prior based on Retinex to decompose an observed image into a reflectance layer and an illumination layer. Different from the existing methods, our proposed model can preserve the reflectance layer with more fine details while enforcing the illumination layer to be texture-less, avoiding the texture- copy problem. Moreover, for solving our nonlinear optimiza- tion, we adopt an alternating minimization scheme to find the optimal. Finally, we test our algorithm on a large number of images and the experimental results illustrate that the pro- posed method has achieved the better result than other state- of-the-art methods both qualitatively and quantitatively.

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PROPOSED METHOD

Let us think back to the assumption of the Retinex theory. It says that the reflectance tends to be piece-wise constant and the illumination is locally smooth. Many methods [1, 2, 3] based on the Retinex theory have been proposed, based on this assumption. They usually regularize the reflectance using the L_1-norm and the illumination using the L_2-norm. In contrast, we adopt the L_2-norm to constraint the reflectance to as far as possible preserve tiny details and the L_p-norm to constraint the illumination to avoid the texture-copy problem. Therefore, we formulate layer decomposition as an energy minimization problem as

$$\min_{r,s} ||i-r-s||^2 + \lambda_r||\nabla r||^2 + \lambda_s||\nabla s||^p + \lambda_b||\nabla s - s_0||^2 , \quad (1)$$

where λ_r, λ_s are the balancing weights for regularizing the reflectance and illumination layers, respectively, ∇ is the gradient operator including horizontal and vertical directions and $||\cdot||^p$ denotes p norm $(0 \leq p \leq 2)$. Note that the L_0-norm ($p = 0$) can result in smoother result, *e.g.*, [4]. We set p to 0.4 in default, and find that it basically meet our demand for texture filtering. The first term $||i-r-s||^2$ is a data term measuring the error between the reconstruct image and the input image. The second term $||\nabla r||^2$ is an L_2-norm term for regularizing the reflectance, the third term $||\nabla s||^p$ term is a p-norm term for regularizing the illumination, and the fourth term $||\nabla s - s_0||^2$ is our bright channel prior term. The constant variable s_0 is defined as $s_0 = \log S_0$, where S_0 is our bright channel intensity of the observed image $\mathbf{I}$. Similar to [5, 6], S_0 can be written as $S_0 = 1 - \min_\Omega \left(\min_{c\in\{r,g,b\}}(1-\mathbf{I})^c\right) = \max_\Omega \left(\max_{c\in\{r,g,b\}} \mathbf{I}^c\right)$, where Ω is a small patch.

Optimization. we adopt a block coordinate descent algorithm to find the optimal solution to the non-convex energy minimization (1). Since the L_p-norm in the regularization term on illumination leads non-smooth optimization, we use an iteratively re-weighted least square method [7] and rewrite the regularization term on illumination as $||\nabla s||^p = u||\nabla s||^2$, where $u = (\nabla s + \epsilon)^{p-2}$ when $0 < p \leq 2$, and

$$u = \begin{cases} \frac{1}{\xi^2}, & \text{if } \ |\nabla s| < \xi \\ \frac{1}{||\nabla s||^2}, & \text{otherwise} \end{cases}, \quad (2)$$

when $p = 0$. We here set to $\xi = \frac{1}{8}$. Note that the variable u is only approximate, since we use a 2-norm format $\Phi(\nabla s; \xi)$ in [8] to approximate the L_0-norm function.

RESULTS 1

1. Ablation study

Figure 1: Algorithm variants. To show the effect of each constraint, we remove different regularization terms. From left to right: input, as described, $\lambda_r = 0$, $\lambda_s = 0$, and $\lambda_b = 0$. Note: **1th row:** reflectance; **2th row:** illumination.

2. Visual comparison for low-light image enhancement

Figure 2: Comparison with other state-of-the-art methods for low-light image enhancement. From left to right: Input,[3],[5],[9], and Ours.