REFLECTANCE ESTIMATION USING MULTIPLE EXPOSURE IMAGES

Yusuke Shirahashi, Ryo Matsuoka and Masahiro Okuda

Univ. of Kitakyushu Faculty of Environmental Engineering Kitakyushu, Japan

ABSTRACT

We introduce a method for intrinsic image decomposition from multiple exposure images. Our method jointly enhance the dynamic range of the images by incoorpolating the multiple exposures and estimate the reflectance and shading components of a scene. Since the reflectance component does not depend the exposure of the images, we estimate a single reflectance component and several shading componets that corresponds to the inputs.

***Index Terms*—** Reflectance, Shading, Intrinsic Image Decomposition, High Dynamic Rnage Images

1. INTRODUCTION

Lumbertian reflectance model assumes that the reflectance (albedo) and shading is expressed by $\widehat{\mathbf{p}} = \widehat{\mathbf{r}} \otimes \widehat{\mathbf{s}}$ where $\widehat{\mathbf{p}} = [\widehat{\mathbf{p}}_R^\top \ \widehat{\mathbf{p}}_G^\top \ \widehat{\mathbf{p}}_B^\top]^\top \in \mathbb{R}^{3N}$ is a vectorized observed color image, where N is the number of the pixels, and $(\cdot)^\top$ stands for the transposition of $(\cdot)$. Also, $\widehat{\mathbf{r}} \in \mathbb{R}^{3N}$ is the reflectance, and $\widehat{\mathbf{s}} \in \mathbb{R}^{3N}$ is the shading, i.e. the illumination falling on this pixel. The operator $\otimes$ is a pixel-wise multiplication. The intrinsic image decomposition's aim is to estimate $\widehat{\mathbf{r}}$ and $\widehat{\mathbf{s}}$ given an input image $\widehat{\mathbf{p}}$. This can be reformulated by taking the log of the images:

$$\mathbf{p} = \mathbf{r} + \mathbf{s}, \tag{1}$$

where $\mathbf{p} = \log \widehat{\mathbf{p}}$ and so on.

Many approaches have been proposed to efficiently solve the decomposition problem. Some of the methods use multiple images of a scene to improve the decomposition performance. We aim to estimate the reflectance and shading components of a scene with high dynamic range from a multiple exposure image set.

Notation: The number of pixels is denoted by N, and all the color images is represented by $3N$ dimentional vectors. The reflectan and shading images are denoted by $\hat{\mathbf{r}} \in \mathbb{R}^{1\times 3N}$ and $\hat{\mathbf{s}}_k \in \mathbb{R}^{1\times N}$. $\hat{\mathbf{u}}_k \in \mathbb{R}^{1\times 3N}$ is a input image set.

2. PROPOSED MEHTOD

First we obtain a single reflectance and multiple shading components from a multiple exposure image set. We assume that illumination is achromatic, and thus the shading component is also achromatic.The obtained reflectance can be regarded as the reflectance of the high dynamic range images derived by integrating the image set. Furthermore we combine the shading images to a single image. We assume that the reflectance lies in a range of [0 1], and the shading has a high dynamic range. Thus the tone-mapping can be performed only by compressing the range of shading.

2.1. Decomposition Problem

Our decomposition algorithm is based on [1]. We achieve it by minimizing the cost function

$$\begin{aligned} &\min_{\mathbf{r},\mathbf{s}_k} \alpha\|\mathbf{D}\mathbf{r}\|_{0,1} + \sum_{k=1}^{3} \lambda_k \|\mathbf{L}\mathbf{s}_\mathbf{k}\|_2^2 + \omega_k \|\mathbf{W}_k\left(\mathbf{u}_k - \mathbf{r} - \mathbf{s}\mathbf{M}'_k\right)\|_2^2 \\ &\text{s.t. } d_i \le r_i \le t_i, d_{k,i} \le s_{k,i} \le t_{k,i}, \text{for}\forall k, \forall j \end{aligned} \tag{2}$$

where $\mathbf{u}_k \in \mathbb{R}^{1\times 3N}$ is the k-exposure of the input images. $\mathbf{r} \in \mathbb{R}^{1\times 3N}$ is the reflectance image of the form$\mathbf{r} = [\mathbf{r}_R^T \, \mathbf{r}_G^T \, \mathbf{r}_B^T]^T$. $\mathbf{s}'_k \in \mathbb{R}^{1\times N}$ is the shading image that corresponds to the k-th exposure image. $\mathbf{D}' \in \mathbb{R}^{2N\times N}$ is a convolution matrix that employs derivative w.r.t. horizontal and vertical directions, and $\mathbf{L} \in \mathbb{R}^{N\times N}$ is a Laplacian convolution matrix. $\mathbf{W}_k \in \mathbb{R}^{N\times N}$ is a weighting matrix, and $\mathbf{M} \in \mathbb{R}^{3N\times N}$ is a matrix to duplicate a vector. α,$\lambda_{1,2,3}$,$\omega_{1,2,3}$ are weights for balancing the terms.

We solve it by alternating direction method for multipliers (ADMM)[2], which is a convex optimization problem. Since Eq.(2) is not convex, it is not guaranteed to converge to the optimal solution, but experimentally we have confirmed that we can obtain sasitfactory results. To apply ADMM, Eq.(2) is converted to

$$\begin{aligned} &\arg \min_{\mathbf{r},\mathbf{s}_{1,2,3},\mathbf{z}_{1,2,3}} \alpha\|\mathbf{z}_1\|_{0,1} \\ &+ \sum_{k=1}^{3} \lambda_k \|\mathbf{L}\mathbf{s}_\mathbf{k}\|_2^2 + \omega_k \|\mathbf{W}_k\left(\mathbf{u}_k - \mathbf{r} - \mathbf{s}_k\right)\|_2^2 \\ &+\beta\|\mathbf{z}_1 - \mathbf{D}\mathbf{r} - \mathbf{b}_1\|_2^2 + \beta\|\mathbf{z}_2 - \mathbf{r} - \mathbf{b}_2\|_2^2 \\ &+ \sum_{i=1}^{3} \beta\|\mathbf{z}_{i+2} - \mathbf{s}_i - \mathbf{b}_{i+2}\|_2^2 + \sum_{i=2}^{5} \iota(\mathbf{z}_i) \end{aligned} \tag{3}$$

where $\mathbf{z}_1 \in \mathbb{R}^{1\times 6N}, \mathbf{z}_2, \mathbf{z}_3, \mathbf{z}_4, \mathbf{z}_5 \in \mathbb{R}^{1\times 3N}$ are auxirialy variables. $\iota(\cdot)$ in (3) is defined by

$$\iota(x_j) = \begin{cases} 0 & (d_j \le x_j \le t_j) \\ +\infty & (otherwise) \end{cases} \tag{4}$$

3. EXPERIMENTAL RESULTS

3.1. Reflectance estimation from multiple exposures

We apply our method to multiple exposure image sets consisting high, middle, and low exposure images. Some of the input images are shown in 1. The result of the intrinsic image decomposition from a multiple exposure set is shown in Fig.2, where the shading image is derived from the middle exposure image. We compare our results with the past work [3]. Since the original method [3] handles only a single image, we extend it so that it can handle the multiple image input. While the reflectance image obtained by the conventional method has a fake color that the original object does not have, the proposed method yields a satisfactory result.

3.2. Tonemapping

Fig.3 shows the tone-mapped HDR images, which are the product of the reflectance and the tone-mapped shading image. We adopt Reinhard's operator [4] for tone-mapping

We calculate the PSNR of the saturation channel of the middle exposure image based on the assumption that the middle exposure image has most natural colorfulness. The result is shown in Table 1, where we use the tone-mapping function as well as the Reinhard's operator. One can see from the figure that the proposed method tone-mappes the hdr with less degration on the saturation.

Table 1: PSNR of saturation

	Reinhard	MATLAB
Proposed method	16.65	19.50
Conventional method	29.67	19.63

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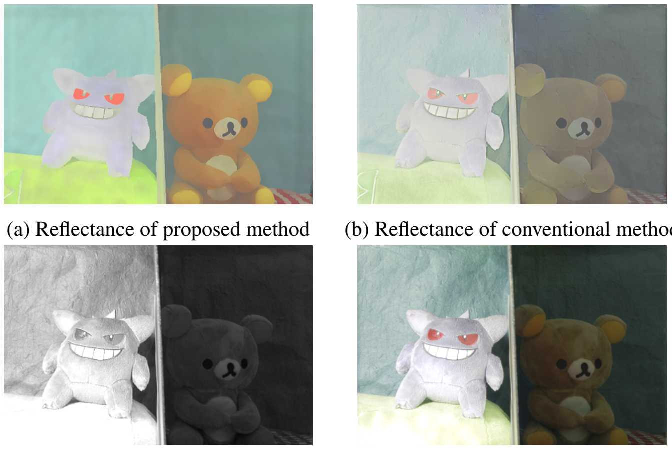
(a) middle exposure image (b) high exposure image

Fig. 1: input image



(a) Reflectance of proposed method (b) Reflectance of conventional method

(c) Shading of proposed method (d) Shading of conventional method

Fig. 2: Decomposition results

(a) Proposed method (b) Conventional method

Fig. 3: Tonemapped by Reinhard's operator

4. REFERENCES

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