REFLECTANCE ESTIMATION AND WHITE BALANCING USING MULTIPLE IMAGES

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ABSTRACT

We propose a novel method for reflectance estimation by using a flash/no-flash image pair. In our method, by using multiple images of the same scene taken under different lighting conditions, we estimate a reflectance component which does not depend on scene illumination, and a shading component caused by illumination lights. Moreover, we apply it to white balance correction by appropriately correcting the estimated shading components. The proposed method achieve better performance than conventional methods especially under colored illumination and mixture lighting conditions.

Index Terms— Reflectance estimation, White balancing, Flash/no-flash image, Image decomposition

1. INTRODUCTION

The intrinsic image model [1] assumes that an image scene is the product of a scene's reflectance (also called albedo) and shading (or illuminant) at each pixel, expressed as $\widehat{\mathbf{p}} = \widehat{\mathbf{r}} \otimes \widehat{\mathbf{s}}$ 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. The decomposition can be applied to many applications such as depth estimation, material recognition and white balancing. There exit many methods on the intrinsic image decomposition [2, 3, 4, 5, 6]. For example, the recent work [5] estimates the reflectance with low computational complexity and obtain satisfactory results by minimizing a cost function that consisits of the prior with a heavy-tailed distribution. Many studies, however, have not focused on mixture lighting scene. Namely, they assume that the photograph was taken under a single illuminant source. Many of them fail when decomposing the image with multiple lighting conditions.

White balancing is an important tool to correct chrominance of images in order to simulate the color consistency in the human visual system. Many white balancing techniques have been proposed [7, 8, 9, 10, 11, 12]. Most of the commercial cameras and photo editing tools involve some practical functionality to recover natural white balance. Unfortunately, most of them cannot realize adequate white balancing results especially for the colored illumination and mixture lighting conditions. Some techniques for the white balancing under the mixed lighting condition have been proposed [11, 12, 13, 14], but these methods require user interaction or more complex and are based on restrictive assumptions. For example, in [13], to correct localized color casts, they use a scribble interface and achieve effective correction. In contrast, [11] proposed a semi-automatic white balance technique for scenes with two light types, but they assume that the illuminant information is known. The recently proposed method [12] achieves a better performance than the other methods even under the mixture light sources, it requires a user interaction.

Meanwhile, the flash/no-flash image pair based image processing [15, 16, 17] have been actively studied, and attracted attention as an effective method to overcome the limitation of the performance of classical single image-based methods. In these methods, the noise-free flash image taken by an electric flash is utilized as a guide image to restore the noisy no-flash image. In addition, in [15], by estimating the scene illumination color from a flash/no-flash image pair, they achieved the white-balancing. However, the method [15] fails and produces an unexpected color artifact under the complex lighting conditions that are considered in this study.

In this paper, we present a novel approach for the reflectance estimation. In general, the estimation of a contribution of each light from a single image is a severely ill-posed problem. We overcome this difficulty by utilizing a flash image as a guidance. Our technique estimates the reflectance component of the specific object color, and the shading component from a flash/no-flash image pair. Then we apply it to the white balance correction by appropriate correction of the shading component. The proposed method achieve a good performance especially under colored illumination and mixture lighting condition.

In Section 2, we discuss the intrinsic image decomposition that is a key technique of the proposed method. Our decomposition problem is formulated by the optimization problem with $\ell_{0,1}$ norm, and a decomposition algorithm that estimates the reflectance and shading components is proposed. In Section 3, several examples are shown to verify the validity of the proposed algorithm, and compare our work to conventional methods. In the last section, we briefly conclude this paper.

Notation: Our method mainly consists of two steps. We treat images in the log domain in the first step, and linear domain in the second step. In the manuscript, we summarize the notation for images $\mathbf{x} = \{\mathbf{p}, \mathbf{r}, \mathbf{s}_1\mathbf{s}_2\}$ as follows

- $\mathbf{x}$: images in the log domain
- $\widehat{\mathbf{x}}$: the linear version of $\mathbf{x}$, that is, $\mathbf{x} = \log \widehat{\mathbf{x}}$
- $\bar{\mathbf{x}}$, $\widetilde{\mathbf{x}}$: images in the linear domain, used in the second step

2. INTRINSIC IMAGE DECOMPOSITION

Our goal is to estimate the reflectance and shading components and to correct its white balance using them. This decomposition is inherently a challenging problem since the equation (1) is severely underdetermined. One solution is to apply tractable prior knowl-

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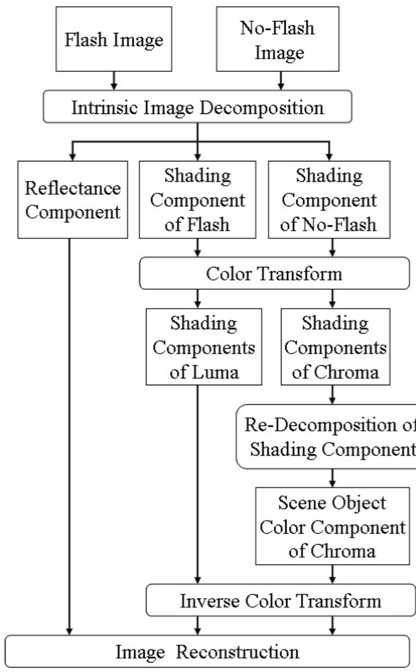


Fig. 1. The flow chart of the proposed method.

edge to solve the problem [3, 5, 18]. Their methods are based on the simple idea that the reflectance of the natural images has piecewise constant regions with sharp edges while the shading component smoothly varies between pixels.

The proposed white balance correction mainly consists of two steps:

1. A single reflectance $\mathbf{r}$ and two shading components $\mathbf{s}_1$, $\mathbf{s}_2$, which correspond to a flash/no-flash image pair $\mathbf{p}_1$, $\mathbf{p}_2$, respectively, are estimated.
2. The estimated shading component $\mathbf{s}_2$ of the no-flash image $\mathbf{p}_2$ is appropriately corrected to eliminate illuminant colors, and then the white balancing is done simply by adding the corrected shading component to the reflectance $\mathbf{r}$.

Figure 1 shows the flow of our method.

2.1. Proposed intrinsic image decomposition problem

The first step of our method decomposes two input images to their reflection and shading components. We assume that the inputs are well aligned and no further registration or motion compensation is needed, and the both of the two inputs have the same reflectance. We find a single reflectance component and two shading components by minimizing the cost function:

$$\min_{\mathbf{r},\mathbf{s}_1,\mathbf{s}_2} \|\mathbf{Dr}\|_{0,1} + \sum_{i=1}^{2} w_{si}\|\mathbf{Ls}_i\|_2^2 + \sum_{i=1}^{2} w_{fi}\|\mathbf{p}_i - (\mathbf{r}+\mathbf{s}_i)\|_2^2,$$
$$\text{s.t. } l_j \le r_j \le u_j,\ \ l_j \le s_{1j} \le u_j,\ \ l_j \le s_{2j} \le u_j,\ \text{for } \forall j, \quad (2)$$

where r_j is a j-th pixel value of $\mathbf{r}$, and so on. $\mathbf{L} = \text{diag}\{\mathbf{L}', \mathbf{L}', \mathbf{L}'\} \in \mathbb{R}^{3N\times 3N}$ is a convolution matrix representing a laplacian operator $\mathbf{L}' \in \mathbb{R}^{N\times N}$, $\mathbf{D} = \text{diag}\{\mathbf{D}', \mathbf{D}', \mathbf{D}'\} \in \mathbb{R}^{6N\times 3N}$ consists of the vertically concatenated first-order difference operators $\mathbf{D}' = [\mathbf{D}_h^\top\ \mathbf{D}_v^\top]^\top \in \mathbb{R}^{2N\times N}$ with horizontal $\mathbf{D}_h \in \mathbb{R}^{N\times N}$ and vertical oprators $\mathbf{D}_v \in \mathbb{R}^{N\times N}$. The two inputs $\mathbf{p}_1 \in \mathbb{R}^{3N}$ and $\mathbf{p}_2 \in \mathbb{R}^{3N}$

Algorithm 1 Algorithm for (4)

flash $\widehat{\mathbf{p}}_1$, and no-flash image $\widehat{\mathbf{p}}_2$ are given, and they are transformed to log domain $\mathbf{p}_1$ and $\mathbf{p}_2$.
set k=0, and chose the weights w_{si}, w_{fi} (i=1,2) and α.
Choose $\mathbf{r}^{(0)}$, $\mathbf{s}_2^{(0)}$, $\mathbf{v}_i^{(0)} (i = 1, 2, 3, 4)$.
while a stop criterion is not satisfied **do**
    $\mathbf{s}_1^{(k+1)} = \arg\min_{\mathbf{s}_1} f(\mathbf{s}_1|\mathbf{r}^{(k)}, \mathbf{s}_2^{(k)}, \mathbf{v}_{1,2,3,4}^{(k)})$
    $\mathbf{s}_2^{(k+1)} = \arg\min_{\mathbf{s}_2} f(\mathbf{s}_2|\mathbf{r}^{(k)}, \mathbf{s}_1^{(k+1)}, \mathbf{v}_{1,2,3,4}^{(k)})$
    $\mathbf{r}^{(k+1)} = \arg\min_{\mathbf{r}} f(\mathbf{r}|\mathbf{s}_1^{(k+1)}, \mathbf{s}_2^{(k+1)}, \mathbf{v}_{1,2,3,4}^{(k)})$
    $\mathbf{v}_{1,2,3,4}^{(k+1)} = \arg\min_{\mathbf{v}_{1,2,3,4}} f(\mathbf{v}_{1,2,3,4}|\mathbf{r}^{(k+1)}, \mathbf{s}_1^{(k+1)}, \mathbf{s}_2^{(k+1)})$
    $\alpha = 2\alpha, \quad k = k+1$
end while

NOTE: $f(a|b)$ indicates the function of the variable a with given b.

are the flash and no-flash images respectively. The norm for the vectorized color images $\|\mathbf{x}\|_{0,1}$ ($\mathbf{x} = [\mathbf{x}_R^\top\ \mathbf{x}_G^\top\ \mathbf{x}_B^\top]^\top$) is defined with the operator $C(m)$, which returns 0 if m is 0, and 1 otherwise, by

$$\|\mathbf{Dr}\|_{0,1} = \sum_j C\left(|\partial_x r_{Rj}| + |\partial_y r_{Rj}| + |\partial_x r_{Gj}| + |\partial_y r_{Gj}| + |\partial_x r_{Bj}| + |\partial_y r_{Bj}|\right), \quad (3)$$

where j is a pixel index. The optimization problem is partially based on the work [5]. Our feature is that we relax the relationship (1) by allowing some reconstruction error and directly find the two shading components, and we use the $\ell_{0,1}$ norm in the first term to treat the *RGB* channels simultaneously. To take account of the properties of the locally flat reflectance, we introduce the ℓ_0 based term in (2). Instead of the simple ℓ_0 norm we use the $\ell_{0,1}$ norm, where we consider the sparseness of the gradients of all the three color channels. By introducing the $\ell_{0,1}$ norm, fake color artifact due to violation of the color balance is relieved, which is important treatment especially for our white balance application. The second term is introduced to satisfy the properties of the shading whose gradient gradually varies. The third term penalizes the decomposition error. To obtain a meaningful solution for $\mathbf{r}$, $\mathbf{s}_1$ and $\mathbf{s}_2$, we consider the constrained problem with the specific range constraint for each pixel of the three images.

Since the cost function is non-convex due to the $\ell_{0,1}$ norm, and there is an inequality constraint, it is impossible to solve it by conventional gradient-based methods. To solve the problem, we introduce auxiliary variables and adopt the penalty function method. By introducing the auxiliary variables $\mathbf{v}_i (i = 1, 2, 3, 4)$, the cost function to minimize in each iteration of the algorithm is given by

$$\min_{\mathbf{r},\mathbf{s}_{1,2},\mathbf{v}_{1,2,3,4}} f(\mathbf{r}, \mathbf{s}_{1,2}, \mathbf{v}_{1,2,3,4}), \quad \text{where}$$
$$f(\mathbf{r}, \mathbf{s}_{1,2}, \mathbf{v}_{1,2,3,4}) = \|\mathbf{v}_1\|_{0,1} + \sum_{i=1}^{2} w_{si}\|\mathbf{Ls}_i\|_2^2 + \sum_{i=1}^{2} w_{fi}\|\mathbf{p}_i - (\mathbf{r}+\mathbf{s}_i)\|_2^2 + \sum_{i=2}^{4}\iota(\mathbf{v}_i) + \alpha\|\mathbf{Dr} - \mathbf{v}_1\|_2^2 + \alpha\|\mathbf{r} - \mathbf{v}_2\|_2^2 + \alpha\|\mathbf{s}_1 - \mathbf{v}_3\|_2^2 + \alpha\|\mathbf{s}_2 - \mathbf{v}_4\|_2^2. \quad (4)$$

$\iota(\cdot)$ is a indicative function, which is defined for each pixel j as

$$\iota(x_j) = \begin{cases} 0, & \text{if } l_j \le x_j \le u_j \\ +\infty & \text{otherwise} \end{cases}, \quad (5)$$

(a) Example 1 (b) Example 2-1 (c) Example 2-2

Fig. 2. Scenes with multiple light sources used in our experiment.

The indicative function guarantees that the optimal solution falls in the range $[l_j, u_j]$. The auxiliary variables $\mathbf{v}_i(i=1,2,3,4)$, are introduced for $\mathbf{Dr}$, $\mathbf{r}$, $\mathbf{s}_1$, and $\mathbf{s}_2$, respectively, and then we add the l_2 penalty terms between the four pairs. The parameter α is a weight that we increase during iterations of the algorithms. As α gets larger, the solution gets closer to the solution of the original cost function (2). We alternately minimize (4) w.r.t. each of the seven variables $\mathbf{r}, \mathbf{s}_1, \mathbf{s}_2, \mathbf{v}_i(i=1,2,3,4)$ with other variables fixed. The algorithm is roughly shown in Algorithm 1. The sub-problem for each of $\mathbf{r}, \mathbf{s}_1, \mathbf{s}_2$ is a simple least squares regression whose solutions can be found by solving a linear equation of a form $\mathbf{Ax} = \mathbf{b}$. Since the matrix $\mathbf{A}$ for the sub-problems is a block circulant matrix with circulant blocks (BCCB), it is diagonalized by FFT, and thus the solution can be quickly calculated. The solution of the sub-problem w.r.t. $\mathbf{v}_1$ is given by applying hard shrinkage to the total sum of the absolute gradients in the *RGB* channels. We find the optimal solutions for $\mathbf{v}_i(i=2,3,4)$ simply by truncating the variables. One can refer the literatures [5, 19, 20, 21] for the detail of the sub-problems.

2.2. White Balance Correction

In the previous section, the reflectance and shading components are calculated by solving the decomposition problem. Next, we discuss the detail of the proposed white balance correction. We assume that scene illumination contains one or a few dominant colors, and the chrominance of the shading has one or a few dominant values. Based on the assumption, we attempt to remove undesired colors from the shading component. We transform the shading components in *the linear scale* $\widehat{\mathbf{s}}_1$ and $\widehat{\mathbf{s}}_2$ to the *YUV* color space. The two chrominance components in the *YUV* color space is denoted by $\widehat{\mathbf{s}}_1^U$, $\widehat{\mathbf{s}}_1^V$, and so on. Then we decompose each of the *U* and *V* components by using

$$\min_{\mathbf{d}^U,\bar{\mathbf{s}}_1^U,\bar{\mathbf{s}}_2^U} \|\mathbf{d}^U\|_0+\sum_{k=1}^{2}\lambda_k\|\mathbf{L}\bar{\mathbf{s}}_k^U\|_2^2+\sum_{k=1}^{2}\beta_k\|\widehat{\mathbf{s}}_k^U-(\mathbf{d}^U+\bar{\mathbf{s}}_k^U)\|_2^2, \quad (6)$$

where $\mathbf{d}^U \in \mathbb{R}^N$ is the chrominance component of a scene object, $\bar{\mathbf{s}}_1^U, \bar{\mathbf{s}}_2^U \in \mathbb{R}^N$ are the chrominance components of the shading component for a flash and a no-flash image respectively. $\widehat{\mathbf{s}}_k^U(k=1,2)$ is the linear-domain version of $\mathbf{s}_k^U$, which is obtained in the previous decomposition step. Here, we assume that the estimated shading component includes an object color information, and we remove it by using ℓ_0-based smoothing. We introduce the second term based on the prior on the shading component. The third term guarantees that the decomposition error is satisfactory small. The same procedure is applied for *V* components to obtain $\mathbf{d}^V$, $\bar{\mathbf{s}}_1^V$, and $\bar{\mathbf{s}}_2^V$. This cost function is again non-convex due to the ℓ_0 norm, and thus we solve it by the penalty function method, which is similar to the procedure in the previous section. The solution is quickly obtained by iteratively applying hard shrinkage and the least squares method enhanced by FFT.

Once the solution for (6) is obtained, the set of smoothed chrominance $\mathbf{d}^U$, $\mathbf{d}^V$, and the illuminance of $\widehat{\mathbf{s}}_2$ is transformed back to the *RGB* space (denoted by $\widetilde{\mathbf{s}}_2$), and then we obtain a final result $\widetilde{\mathbf{p}}$ is obtained by :

$$\widetilde{\mathbf{p}} = \widehat{\mathbf{r}} \otimes \widetilde{\mathbf{s}}_2,$$

where $\widehat{\mathbf{r}}$ is the images in the linear domain obtained in the last section. We show the results of the optimization (6) of the second step in Fig. 3 for the image Fig. 2(a).

Fig. 3. The results of the second step: (top: left to right) $\bar{\mathbf{s}}_1^U$, $\bar{\mathbf{s}}_2^U$, $\mathbf{d}^U$, (bottom: left to right) $\bar{\mathbf{s}}_1^V$, $\bar{\mathbf{s}}_2^V$, $\mathbf{d}^V$.

Fig. 4. Weiss [2] + Retinex [22]: the result is obtained using a flash/no-flash image pair, (left) Reflectance, (right) Shading of the flash image.

3. EXPERIMENTAL RESULTS

We apply the proposed method to a variety of flash/no-flash image pairs under the mixture lighting conditions. The use of multiple images makes the decomposition easier than a single image. Weiss [2] also takes advantage of it, and Grosse et al.'s paper [3] shows that the method [2] with Retinex algorithm [22] outperforms other conventional methods at that time. However, as shown in Fig. 4, which is derived by Weiss's algorithm with Retinex [3] [1], the algorithm often fails since only the two images are inadequate and require more images. Moreover as the method handles only edges, it does not work well when input images have different colors like flash/no-flash images. Thus we adopt [23] and a modified version of Li et al.'s method [5] for comparison, which is described in the next example.

Since it requires a heavy effort (or even impossible in many cases) to obtain ground truth of reflectance components, it is difficult to precisely perform quantitative comparison. On the other hand, white balancing of images under colored and multiple light sources is an appropriate application to evaluate the preciseness of the intrinsic image decomposition, since a precise decomposition will cancel color artifacts caused by the light. In the section, we show some comparison with figures for the decomposition and white balancing.

3.1. Example 1

First we apply our method to a flash/no-flash image pair (shown in Fig. 2 (a)), which is used in [15]. We compare our result with the

[1] We use the author-provided software [3].

Proposed Method

Two-input version of [5]

Fig. 5. Example 1: (left to right) Reflectance, Shading of flash image, Shading of no-flash image, Final white-balanced result, and Close-up of the result.

recently proposed image decomposition method [5]. Although the method [5] is not designed for white balancing, it is reasonable to compare with it to show the validity of our algorithm. For fair comparison, we slightly change the method [5] to handle two inputs, that is, the minimization problem used in the method is modified to

$$\min_{\mathbf{r}} \rho(\mathbf{Dr}) + \lambda \sum_{i=1}^{2} \|\mathbf{L}(\mathbf{p}_i - \mathbf{r})\|_2^2,$$

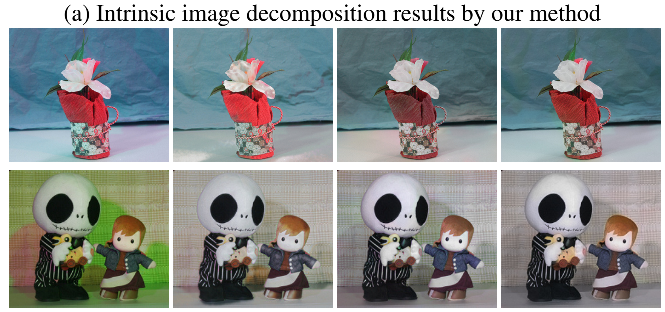
where $\rho(\cdot)$ is a function that represents the Gaussian-like distribution with long tail (see [5], for detail). This problem is essentially the two-input version of [5]. After this optimization, we obtain results of the conventional method by adopting only the luminance of the obtained shading component and then adding it back to the reflectance. Fig. 5 shows the resultant reflectance $\widehat{\mathbf{r}}$, shading $\widehat{\mathbf{s}}_1$ and $\widehat{\mathbf{s}}_2$, the final white-balanced image, and its close-up. The original scene contains reddish illumination. Our results can successfully remove undesired illumination and obtain more natural look than the conventional method.

3.2. Example 2

In this experiment, we prepare a pair of input images with no positional displacement by using a tripod. We use CANON EOS 20D. The white balance setting of the camera is fixed to auto white balance (AWB). In Fig. 2(b), (c), we show an image under the mixture lighting condition with different color lights. This scene has two color lights. From Fig. 2(b), (c), it can be seen that the AWB of the camera is inadequate under the complex environmental lights.

For comparison, we take an image with in-camera manual white balancing mode, which estimates a white point using an image of a white object photographed in advance. We show the decomposition results obtained by the proposed method in Fig. 6(a) and the white-balanced results of the conventional method and the manual white balance (MWB) mode and [23]. In [23], the white-balancing is achieved by the color distribution transfer from a flash image into a no-flash image. While the greenish and reddish colors remain in the results of the MWB and [23] and [5], our method can estimate the reflectance and shading component from a flash/no-flash image pairs with high accuracy and removes color illuminance more than the others.

(a) Intrinsic image decomposition results by our method



(b) White-balanced results

Fig. 6. Example 2: (a) Intrinsic image decomposition results of (left to right) Reflectance, Shading of flash, and Shading of no-flash obtained by our method, (b) The final results of (left to right) MWB, [23], [5] , and Our method.

4. CONCLUSION

In this paper, we proposed the novel white balancing technique. The proposed method consists of two-step approach. In the first step, we estimate the reflectance and the shading components from the flash/no-flash image pairs by applying intrinsic image decomposition. In the second step, we eliminate the color component of each estimated shading. Then we achieve the white balancing where the corrected image are reconstructed by using the reflectance component and appropriately corrected shading components. From experimental results, it was shown that the proposed method can be achieved better performance under the mixture lighting conditions.

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