

Multispectral Image Intrinsic Decomposition via Subspace Constraint

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Abstract

Multispectral images contain many clues of surface characteristics of the objects, thus can be used in many computer vision tasks, e.g., recolorization and segmentation. However, due to the complex geometry structure of natural scenes, the spectra curves of the same surface can look very different under different illuminations and from different angles. In this paper, a new Multispectral Image Intrinsic Decomposition model (MIID) is presented to decompose the shading and reflectance from a single multispectral image. We extend the Retinex model, which is proposed for RGB image intrinsic decomposition, for multispectral domain. Based on this, a subspace constraint is introduced to both the shading and reflectance spectral space to reduce the ill-posedness of the problem and make the problem solvable. A dataset of 22 scenes is given with the ground truth of shadings and reflectance to facilitate objective evaluations. The experiments demonstrate the effectiveness of the proposed method.

1. Introduction

The observed spectrum of a single pixel is determined by illumination, reflectance and geometry. Shading image contains illumination condition and geometry information, while reflectance image contains the material reflectance property, which is invariant to light condition and shadow effect. The decomposition problem has been a long standing problem in both computer graphics and computer vision applications. For instance, shape-from-shading algorithms could benefit from an image with only shading effects, while image segmentation would be easier in a world without cast shadows.

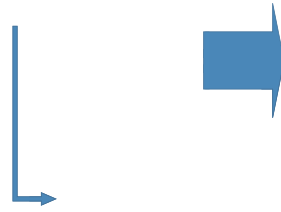
Obviously, intrinsic image decomposition is an ill-posed problem, since there are more unknowns than observations.

In order to solve this problem, many works [30, 31, 12] focus on sparse representation spatially, but this does not hold for images in general. This paper addressed the problem of the recovery of reflectance and shading from a single multispectral image, namely, the Intrinsic Image Decomposition problem of a whole multispectral image captured under general spectral illumination, hereafter referred to as the IID problem. This problem is worth exploring since geometry and reflectance information are useful under certain circumstances, but one of them always interferes the detection of the other one. Unfortunately, growing dimensions of data make this problem harder to cope with.

The subspace constraint that we propose is based on the assumption that the reflectance and shading vectors both live in a low dimensional subspace along the spectral domain. According to the inherent nature of the multispectral image, we derive shading basis on the knowledge of illumination condition and derive the reflectance subspace basis by means of principle component analysis (PCA). Assuming that the Retinex theory [23] would continue to take effect in multispectral domain, we propose a subspace-based model so that deriving reflectance and shading from a multispectral image can be modelled as an convex optimization problem. In a significant departure from the conventional approaches which operate in the logarithmic domain, we directly operate on the image domain. The flowchart of our proposed MIID algorithm is shown in Fig. 1.

To overcome the lack of ground truth data of shading and reflectance, we provide a ground-truth dataset for multispectral intrinsic images to enable quantitative evaluation of various intrinsic decomposition methods. Quantitative and qualitative experiments on our dataset have demonstrated that the performance of the MIID method is better than prior work for multispectral images. Our work can bring merits to multiple applications, such as recolorization, relighting, scene reconstruction and image segmentation.

Our major contribution can be summarized as follows:



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subspace model of reflectance is introduced by [26, 29, 37]. With ground truth reflectance and illumination spectra, we can derive their subspace basis vectors and solve the subspace approximations of the true reflectance and shading images effectively.

Dataset. To establish ground-truth for intrinsic images, Tappen et al. [33] created small sets of both computer-generated and real intrinsic images with three color components. The computer-generated images consisted of shaded ellipsoids with piecewise-constant reflectance. The real images were created using green marker on crumpled papers [32]. Grosse et al. [15] provided a large dataset with three color components which is widely used in following analysis. Bell et al. [6] also introduced Intrinsic Images in the Wild, a large scale, public dataset of color images for evaluating intrinsic image decompositions of indoor scenes. Going beyond the three color components, [35, 10] provided a set of multispectral images of various objects without ground truth of reflectance images, and Chen et al. [12] built a dataset with low spectral resolution and limited diversity in image content. To the best of our knowledge, there are no other public multispectral image datasets with ground truth for multispectral image intrinsic decomposition.

3. Our Model

We assume the object surface as Lambertian and hence has diffuse reflection. In most prior work on intrinsic image decomposition, the captured luminance spectrum at every point I_p is modelled as the element-wise product of Lambertian reflectance spectrum r_p and shading spectrum s_p , where s_p is used to characterize the combined effect of object geometry, illumination, occlusion and shadowing. Mathematically, this model can be expressed as

$$I_p = s_p \cdot r_p \quad (1)$$

where I_p , r_p and s_p are all vectors with dimensions equal to the number of spectral bands, K , of the captured image, \cdot denotes element-wise multiplication. The problem is to derive s_p and r_p from observed multispectral luminance vector I_p . At first, we will focus on recovering the reflectance spectrum using this model. Once r_p is determined, the shading image can be derived by point-wise division.

Different from the conventional approaches which operate in the logarithmic domain, we directly formulate the problem in the image domain, and this can overcome numerical problems caused by the logarithmic transformation of the image values, where noise in pixels with low intensity values can lead to large variations. Besides, although there have been substantial evidence of the subspace of the reflectance, it is not clear whether the logarithmically transformed reflectance still lives in a subspace. This makes it

hard to incorporate the subspace prior in formulations based on log-transformed images.

3.1. Estimate Reflectance or Shading Independently

The Retinex model makes following two important observations:

- 1) When there is significant reflectance change between two adjacent pixels p and q , the shading is typically constant. This leads to the relation $I_p \cdot / I_q = r_p \cdot / r_q$, where $\cdot /$ denotes element-wise division;
- 2) When the expected reflectance difference between two pixels is small, the recovered reflectance difference between the two pixels should be small.

Noting that the ratio relationship in observation 1), the ratio relationship can be written as $I_p \cdot r_q = I_q \cdot r_p$, or $L_p r_q = L_q r_p$ where L_p is a diagonal matrix consisting of spectral elements in I_p , we can formulate the problem of recovering the reflectance image as minimizing a weighted sum of the two energy functions:

$$E_{\text{refl}} = \sum_{p,q \in N_{sc}} w_{p,q} (L_p r_q - L_q r_p)^d + \sum_{p,q \in N_{rc}} v_{p,q} (r_p - r_q)^d \quad (2)$$

where N_{sc} denotes shading neighborhood pair sets, N_{rc} denotes reflectance neighborhood pair sets and $w_{p,q}$ and $v_{p,q}$ denote weights. $w_{p,q}$ should be large but $v_{p,q}$ be small when the expected reflectance difference between two adjacent pixels p and q is large, and vice versa. To make the formulation general, we use d to indicate the error norm.

If we directly solve for r_p , the above energy function can be written as the sum of K terms, one for each spectral component and each term can be separately minimized. With a little exercise, it can be shown that the minimal is achieved exactly when $r_p = I_p$; This is due to the inherent ambiguity of the problem, when no other constraints are imposed on r_p . We reduce the ambiguity by exploiting the fact that the reflectance spectra of typical object surfaces live in a low dimensional subspace of \mathbb{R}^K , so that any reflectance vector can be written as a linear combination of J_r basis, with $J_r < K$.

Let B_r represent the $K \times J_r$ basis matrix for representing the reflectance vector, r_p can be written as $r_p = B_r \tilde{r}_p$. The energy function in Eq.(2) now becomes:

$$E_{\text{refl}} = \sum_{p,q \in N_{sc}} w_{p,q} (L_p B_r \tilde{r}_q - L_q B_r \tilde{r}_p)^d + \sum_{p,q \in N_{rc}} v_{p,q} (B_r \tilde{r}_p - B_r \tilde{r}_q)^d \quad (3)$$

The combined energy can be represented in a matrix form as:

$$E_{\text{refl}} = W_{L,B_r} R^d + V_{B_r} R^d \quad (4)$$

where R consists of r_p for all pixels in a vector. The matrix W_{L,B_r} depends on the neighborhood N_{sc} considered,

the weight $w_{p,q}$, the reflectance basis B_r used, and importantly the luminance data I_p ; whereas the matrix V_{B_r} depends on the neighborhood N_{rc} considered, the weight $v_{p,q}$ and the reflectance basis B_r used. Therefore, with this non-logarithmic formulation, we encode the constraint due to the measured luminance data in the matrix W_{L,B_r} .

The ambiguity with the scaling factor is inherent in all intrinsic image decomposition problems since only the product of reflectance and shading is known. To circumvent the ambiguity about the scaling factor, we further assume that the reflectance have small deviation from the input image and add a scale constraint along the entire image as $M_{B_r}R = C_r$, and augment the original energy function to enforce this constraint:

$$E_{\text{refl}} = W_{L,B_r}R_d^d + \lambda_1 V_{B_r}R_d^d + \lambda_2 M_{B_r}R - C_r_d^d \quad (5)$$

where M_{B_r} is a block-diagonal matrix depending on B_r , and C_r is a long vector consisting of luminance coefficient vectors of all I_p .

Similarly, the subspace of the shading is also widely acknowledged and exploited in prior work [14]. Shading inherently lives in a subspace, because there are usually only a few lighting sources with different illumination spectra acting in each captured scene, and the shading effect due to geometry and shadowing only modifies the spectra by a location-dependent scalar. If there is a single illumination source and its spectrum is known or is able to be identified by method of [37], we will use this spectrum(after normalization) as the only shading basis vector ($J_s = 1$ and B_s equals to this normalized spectrum). Likewise the problem of recovering the shading image can be formulate as minimizing

$$E_{\text{shad}} = W_{B_s}S_d^d + \lambda_1 V_{L,B_s}S_d^d + \lambda_2 M_{B_s}S - C_s_d^d \quad (6)$$

3.2. Simultaneous Recovery

Based on the formulation that solves reflectance and shading respectively, we propose an optimization algorithm that simultaneously solves both shading and reflectance. We assume that the subspace of the shading and reflectance are known, represented by basis matrices B_s and B_r , respectively, so that $s_p = B_s s_p$ and $r_p = B_r r_p$. We will use S to denote the long vector consisting of shading coefficient vectors s_p at all pixels, and R to denote the long vector consisting of reflectance coefficient vectors r_p . We propose to solve s_p and r_p , or equivalently S and R , by minimizing a weighted average of the following energy terms.

When shading is expected to be similar in pixels p and q , we have $s_p = s_q$ and $I_p = r_q = I_q = r_p$, or $L_p r_q = L_q r_p$, where L_p is a diagonal matrix consisting of spectral

elements in I_p . We formulate the energy functions directly:

$$\begin{aligned} E_{\text{sc}} &= \sum_{p,q \in N_{sc}} w_{p,q} (L_p r_q - L_q r_p)_d^d + \sum_{p,q} w_{p,q} (s_p - s_q)_d^d \\ &= W_{L,B_r}R_d^d + W_{B_s}S_d^d \end{aligned} \quad (7)$$

When reflectance is expected to be similar in pixels p and q , we have $r_p = r_q$ and $I_p = s_q = I_q = s_p$, leading to a regularization energy

$$\begin{aligned} E_{\text{rc}} &= \sum_{p,q \in N_{rc}} v_{p,q} (L_p s_q - L_q s_p)_d^d + \sum_{p,q} v_{p,q} (r_p - r_q)_d^d \\ &= V_{L,B_s}S_d^d + V_{B_r}R_d^d \end{aligned} \quad (8)$$

The inherent data constraint $I_p = s_p = r_p$ leads to another energy function:

$$\begin{aligned} E_{\text{data}} &= \sum_p s_p \cdot r_p - I_p_d^d = Q_S R - L_d^d \\ &= Q_R S - L_d^d \end{aligned} \quad (9)$$

where Q_S is a block diagonal matrix that depends on the solution for S and the basis matrices B_s and B_r (likewise Q_R), and L is a diagonal matrix consisting of spectral elements of all input pixels.

The problem is to find S and R that minimizes a weighted average of the three energy functions:

$$\begin{aligned} E &= W_{L,B_r}R_d^d + W_{B_s}S_d^d + \lambda_1 V_{L,B_s}S_d^d + V_{B_r}R_d^d \\ &+ \lambda_{\text{data},1} Q_S R - L_d^d + \lambda_{\text{data},2} Q_R S - L_d^d \end{aligned} \quad (10)$$

Direct solution of the above problem solving R and S simultaneously is hard because of the bilinear nature of the data term. We apply the iterative solution, where we solve R and S using alternating projection. As the dimension of the shading subspace is likely to be smaller than the dimension of the reflectance subspace, we solve the shading S first. Also there are typically more subregions in an image with similar reflectance, where it is easier to use the constant reflectance constraint to resolve the ambiguity about shading.

A challenging issue is how to provide initial estimation of S and R in order to effectuate the data constraint in Eq.(9). We first obtain an initial estimate of S by minimizing Eq.(6), based on an assumed B_s . We then add a data constraint to Eq.(5) and determine R by minimizing:

$$\begin{aligned} E_{\text{refl}} &= W_{L,B_r}R_d^d + \lambda_1 V_{B_r}R_d^d + \\ &\lambda_2 M_{B_r}R - C_r_d^d + \lambda_{\text{data},1} Q_S R - L_d^d \end{aligned} \quad (11)$$

to satisfy the data constraint. Finally, S and R are estimated iteratively by minimizing Eq.(10).

More specifically, the whole recovery algorithm is summarized in Algorithm 1:

Algorithm 1: MIID algorithm

- 1 Step 1: Get B_s from the ground-truth illumination and B_r from Munsell colors matt [25].
 - 2 Step 2: Assign constant-shading weights $w_{p,q}$ and constant-reflectance weights $v_{p,q}$ based on the observed multispectral images.
 - 3 Step 3: Solve an initial subspace estimate of the shading vector S by minimizing Eq.(6).
 - 4 Step 4: Solve an initial subspace reflectance vector R by minimizing Eq.(11).
 - 5 repeat
 - 6 Step 5: Solve S by minimizing the energy function in Eq.(10) with $data,1 = 0$, and using previously solved R .
 - 7 Step 6: Solve R by minimizing the energy function in Eq.(10) with $data,2 = 0$, and using previously solved S .
 - 8 until maximum number of iterations (100) is reached or the change in the energy function in Eq.(10) is below a threshold (0.01);
 - 9 Step 7: Reconstruct S and R .
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4. Details

4.1. Weight Choice

Images suffering from poor light condition may contain shadow area, which would in turn bring in unnecessary edges that confuse the algorithm. Various methods are used to determined weights $w_{p,q}$ and $v_{p,q}$, including pixel gradient [14, 21, 23], hue [36], correlation between vectors [19] and learning [33]. To set the weight, we assume that the reflectance of two pixels are similar if their normalized luminances are similar, which can be measured by the correlation of the normalized luminances. Therefore, we proposed a illumination-robust and compute-friendly distance – normalized cosine distance, to measure the differences between spectra of two pixels in one neighborhood. This distance can be formulated as

$$d_{p,q} = 1 - \frac{I_p \cdot I_q}{|I_p| \cdot |I_q|} \quad (12)$$

$d_{p,q}$ is 0 when pixel p and q have same spectra, and increases when spectra of p and q are different. In order to derive weight $w_{p,q}$, we need to further magnify the difference between homogeneous and heterogeneous pixels and make it more robust to the noise. In our implementation

$$w_{p,q} = \frac{1}{1 + e^{-(d_{p,q})^\alpha}} \quad v_{p,q} = 1 - w_{p,q} \quad (13)$$

and α are parameters of sigmoid function. To set α and β , we sample values of α within [1000, 10000] and values

of β within $[10^{-5}, 10^{-2}]$ and choose the combination that performs best.

Fig. 2 shows different separation results for different beta values. If β is too small, shading tends to be more blurred; when β is too big, reflectance would be blurred.

4.2. Subspace Bases for the Shading and Reflectance Spectra

An important step in our problem formulation is to derive subspace basis matrices for the shading and reflectance spectra, respectively. With the help of multispectral imaging systems as PMIS [9] and CASSI [1], we can successfully get growth-truth illumination spectra. Also, there are plenty of works referring to how to extract illumination from images. For example, [37] can be applied in multi-spectral domain and performs well in implementation. In order not to complicate our method, we assume that the shading component is dominated by a single illumination source and we directly determine the shading subspace matrix B_s by using the growth-truth illumination.

For reflectance, the authors of [26, 29] have found J_r to be around 8 so as to reach the best trade-off between expression power and noise resistance in the process of fitting reflectance spectra. We set J_r to be 8 and perform Principle Component Analysis (PCA) to derive B_r from the Munsell colors matt measured by Hiltunen [25], which composes the reflectance spectra of 1269 matt Munsell color chips.

4.3. Initial Estimation

We use L2 norm for all terms, so that solving Eq.(6) or Eq.(11) is a quadratic programming problem, and can be solved efficiently using conjugate gradient method. In Algorithm 1, The solution to the unconstrained optimization problem in Step 3 satisfies the following linear equation:

$$H_s = W_{B_s}^T W_{B_s} + \beta_1 V_{L,B_s}^T V_{L,B_s} + \beta_2 M_{B_s}^T M_{B_s} \quad (14)$$

$$H_s S = \beta_2 M_{B_s}^T C_s$$

In Step 4, the linear equation can be written as

$$H_r = W_{L,B_r}^T W_{L,B_r} + \beta_1 V_{B_r}^T V_{B_r} + \beta_2 M_{B_r}^T M_{B_r} + data,1 Q_s^T Q_s$$

$$H_r R = data,1 Q_s^T L + \beta_2 M_{B_r}^T C \quad (15)$$

Because the matrix H_s and H_r is self-adjoint and sparse, we can solve this equation iteratively, which typically converges very fast. Once the parameters are preoptimized in a given data category, the estimation performance stays stable. On our dataset, we set $\beta_1 = 100$, $\beta_2 = 0.1$ and $data,1 = 10$ empirically.

4.4. Iteration Performance

We use alternating projection to get refined shading and reflectance. Just like what we stated in Step 5 and Step

*c+ $\sqrt{1.6086e-5}$

*d+ $\sqrt{1.4037e-6}$

*e+ $\sqrt{1.3e-7}$

Figure 2. Estimated Reflectance and shading images using different settings for σ . σ is set to be 5000. (b) achieves good result while shading and reflectance overlap clearly in (a) and (c).

6 in Algorithm 1, we update shading first and then the reflectance. In each round of iteration, gradient descent method is applied to solve Eq.(10), with either S or R as unknowns. The iteration stops whenever it reaches the maximum iteration times 100 or when the error gradient $E < 0.01$.

We use LMSE to measure shading and reflectance images. Given the true and estimated images I and \hat{I} , [15] defined LMSE as the MSE summed over all local windows w of size $k \times k$ and spaced in steps of $k/2$:

$$LMSE_k(I, \hat{I}) = \sum_w MSE(I_w, \hat{I}_w) = \sum_w \|I_w - \hat{I}_w\|^2 \quad (16)$$

where $\hat{I}_w = \arg \min \hat{I}_w - \hat{I}_w^2$.

Fig. 3 demonstrates the iteration performance of our algorithm. The energy cost function Eq.(10) decreases with increasing iterations. Before the iteration, the color patches can still be seen clearly; while the shading image tends to be more uniform after iteration.



the light source is iodine-tungsten lamp (that interprets why shading images are a little yellowish). We apply the advanced spectrometer PMIS [9] to acquire the multispectral scenes, which could provide higher resolution in spectral data ranging from 450nm-700nm with 118 spectral channels. Compared with the dataset provided by [12], ours has 17 more scenes with higher resolution, more bands and more details, which enables the dataset to show further and potential applications in other vision researches.

Here, we evaluate our algorithm via our proposed dataset and use LMSE from the ground truth to validate our algorithm quantitatively. Compared with ground-truth, decomposition results that we achieved are desirable in terms of both the LMSE and the visual quality of the decomposed reflectance and shading results.

We display 4 examples from our dataset. The corresponding visualized RGB images for reflectance and shading are listed in Fig. 6. It is clear that our method could produce better decomposition results. In [12], superpixel-based method would lose detail information, while ours is more piecewise constant. We like to emphasize that we did all the image processing and metric computations of LMSE on down-sampled 30 out of 118 spectral channels which corresponds to the setting in [12].

Table 2. Performance statistics for dataset image

| Name | SIID [12] | Ours | Name | SIID | Ours |
|-----------|-----------|-------|----------|-------|-------|
| box | 0.032 | 0.023 | ali | 0.018 | 0.015 |
| cup | 0.016 | 0.012 | greenpig | 0.013 | 0.009 |
| car | 0.025 | 0.012 | mask | 0.005 | 0.004 |
| bottle1 | 0.062 | 0.031 | piggy | 0.012 | 0.008 |
| bottle2 | 0.005 | 0.008 | pumpkin | 0.009 | 0.008 |
| bottle3 | 0.009 | 0.009 | dinosaur | 0.012 | 0.006 |
| bus | 0.030 | 0.031 | horse | 0.021 | 0.012 |
| car2 | 0.030 | 0.024 | kitty | 0.026 | 0.019 |
| dinosaur2 | 0.021 | 0.023 | cap | 0.027 | 0.024 |
| minion | 0.020 | 0.018 | girl | 0.020 | 0.013 |
| plane | 0.024 | 0.015 | train | 0.017 | 0.015 |
| | | | Avg. | 0.021 | 0.015 |

In table 2, we demonstrate the performance for the entire dataset. Here SIID denotes latest spectral intrinsic image decomposition in [12]. Our algorithm outperforms SIID in 19 out of 22 cases, and ours demonstrates a great improvement on average LMSE. Moreover, We note that our method is faster, more memory-friendly and is able to process larger images with more spectral bands.

In addition to evaluate the accuracy for reflectance image recovery in all spectral bands, we compare the spectral curves of selected image points from the ground truth and our algorithm. we choose patches in some scenes of our ground truth. In Fig. 5, it is obvious that our reflectance matches well with the ground truth which means we could gain accurate spectral reflectance with better performance in computation.

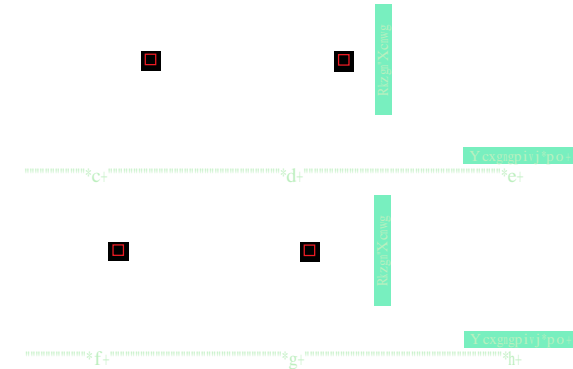


Figure 5. (a)(d) are ground truth reflectance of our dataset, (b)(e) are reflectance images of our results, and the (c)(f) are spectra curve of marked area (solid red: ours; dotted black: ground-truth).

5.3. Experiments on Nayar Multispectral Image Database[35]

To demonstrate the benefit of the subspace constraint, we compare results with and without it using Nayar Multispectral Image Database [35]. We strengthen the constraints of the ‘without’ one to make it solvable. In Fig. 7, the shading images with constraint are more uniform, thus reflectance images are closer to true material reflectance. From the comparison, we see that the subspace constraint helps solve the overlap between the shading and reflectance.

6. Conclusion

We have addressed the problem of the recovery of reflectance and shading from a single multispectral image captured under general spectral illumination. We have applied a subspace constraint to both the reflectance and shading space to solve the multispectral image intrinsic decomposition problem, which significantly reduce the ambiguity. Gradient descent has been used to give the initial estimation of reflectance and shading, and alternating projection method has been applied to solve the bilinear problem. Experiments on multiple datasets demonstrate that the performance of our work is better than prior works in multispectral domain.

Our work has left out constraints on global structure. Retinex theory fails to take effect when both shading and reflectance change extensively in local area. Since the high dimension of multispectral data would complicate the global constraint and bring tremendous computation cost than traditional RGB case, we hope that we will implement the global constraint with more computational efficiency (e.g. parallel design) in the near future.

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Figure 6. Results on sample images from our dataset. (a) are ground-truth reflectance and shading from our dataset, (b) are results derived from SIID [12], and (c) are our results. Note that results are rendered in RGB.

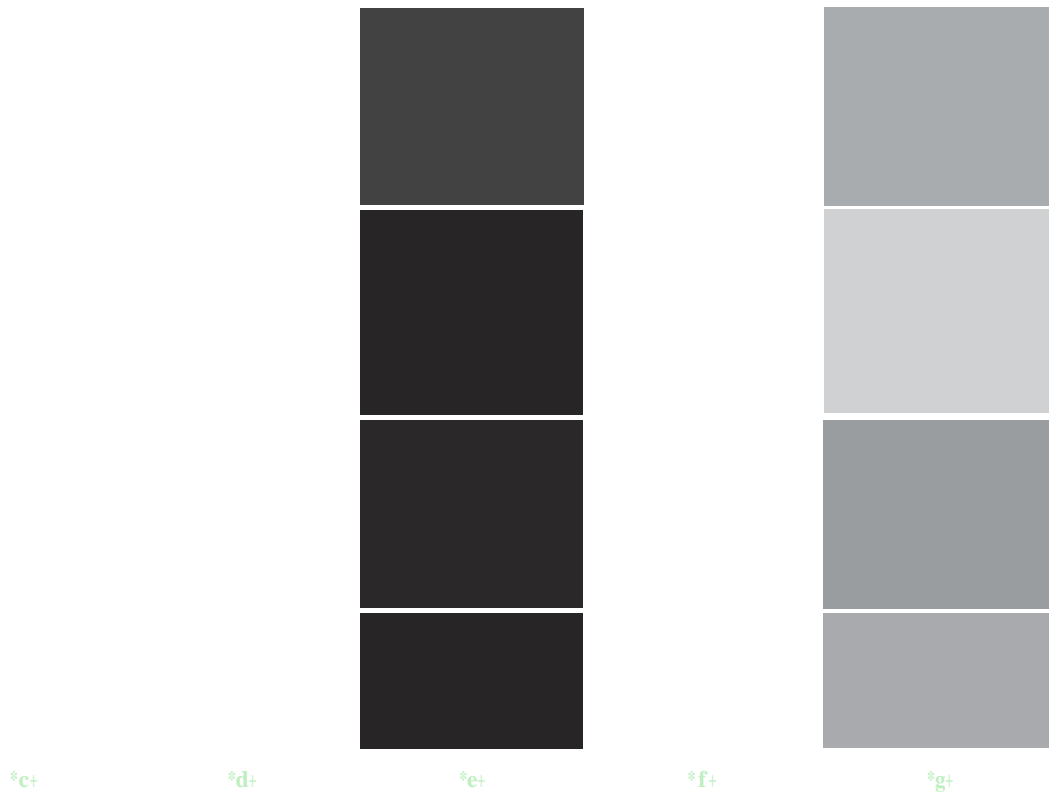


Figure 7. Comparison of decomposition without and with the subspace constraint. (a) Multispectral images (rendered in RGB) Nayar dataset [35]. (b)-(c) show the reflectance and shading components computed without the subspace constraint. (d)-(e) are with the constraint.

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