NMF-Based Spectral Reflectance Estimation from Image Pairs Including Near-Infrared Components

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Abstract—In this paper, a novel spectral reflectance estimation method from image pairs including near-infrared components based on non-negative matrix factorization (NMF) is presented. The proposed method enables estimation of spectral reflectance from only two kinds of input images: an image including both visible light components and near-infrared (NIR) components and an image including only NIR components. These two images can be easily obtained by using a general digital camera without an infrared-cut filter and one with a visible light-cut filter, respectively. Since RGB values of these images are obtained according to spectral sensitivity of the image sensor, the spectrum power distribution of the light source and the spectral reflectance, we have to solve the inverse problem for estimating the spectral reflectance. Therefore, our method approximates spectral reflectance by a linear combination of several bases obtained by applying NMF to a known spectral reflectance dataset. Then estimation of the optimal solution to the above problem becomes feasible based on this approximation. In the proposed method, NMF is used for obtaining the bases used in this approximation from a characteristic that the spectral reflectance is a non-negative component. Furthermore, the proposed method realizes simple approximation of the spectrum power distribution of the light source with direct and scattered light components. Therefore, estimation of spectral reflectance becomes feasible by using the spectrum power distribution of the light source in our method. In the last part of this paper, we show some simulation results to verify the performance of the proposed method. The effectiveness of the proposed method is also shown by using the method for several applications that are closely related to spectral reflectance estimation. Although our method is based on a simple scheme, it is the first method that realizes the estimation of the spectral reflectance and the spectrum power distribution of the light source from the above two kinds of images taken by general digital cameras and provides breakthroughs to several fundamental applications.

Index Terms—Spectral reflectance estimation, near-infrared components, non-negative matrix factorization, color correction, green plant detection.

I. INTRODUCTION

ESTIMATION of spectral reflectance is a very important task since it enables performance improvements of several fundamental applications in the field of image processing. Spectral reflectance includes both visible light components and near-infrared (NIR) components. It is well known that performance of video surveillance in night vision can be improved by monitoring NIR components that can be obtained from spectral reflectance [1]–[4]. Furthermore, spectral reflectance estimation will contribute to the realization of a camera that does not use an infrared-cut filter (IRCF). Since general image sensors have sensitivity for NIR components in the range of 700nm–1000nm as well as visible light components, an IRCF for removing NIR components is necessary to obtain images including only visible light components with high color productivity. If images including only visible light components can be obtained without using an IRCF, drastic improvements such as miniaturization of cameras, cost reduction and image acquisition without flash lights in night scenes will be possible. Although studies on improvement in color reproducivity have been carried out [4], the results have not been satisfactory. On the other hand, if we can directly estimate spectral reflectance with the spectrum power distribution of the light source, this problem can be effectively solved since NIR components can be easily estimated. It is also known that estimation of NIR components can contribute to dehazing from images taken by digital cameras [5].

In addition to the above applications, estimation of the spectral reflectance of objects enables acquisition of their intrinsic color information which does not depend on light conditions [6], [7]. Then generation of new images in different light conditions can be realized. Furthermore, by estimating the spectral reflectance of objects, improvement in the performance of extracting specific objects such as green plants [8]–[10] becomes feasible. For example, if we only use color values in RGB channels for extraction of green plants, not only green plants but also other green objects are detected. On the other hand, by using the spectral reflectance of objects, we can distinguish those different objects, and the extraction performance can be improved. In this way, estimation of spectral reflectance including both visible and NIR components is important for improving the performance of many fundamental applications.

Generally, in order to extract spectral reflectance including both visible and NIR light components, conventional methods require the use of special devices such as multi-spectral cameras. If such special devices cannot be used, estimation of spectral reflectance becomes difficult. Therefore, if estimation becomes feasible by only using images taken by equipment that has the same structure as that of general digital cameras, it will lead to several technical breakthroughs.

There have been proposed several methods that enable the spectral reflectance estimation from RGB values taken by general digital cameras. Generally, since the dimension of the RGB values of each pixel is lower than that of the
spectral reflectance, the spectral reflectance estimation is one of the ill-posed problems. Various studies, which estimate unique solutions for such ill-posed problems by introducing some prior information, have been carried out in the field of image processing. For example, methods including new regularization terms and methods performing low-dimensional subspace approximation based on multivariate analysis such as principal component analysis (PCA) [11], kernel PCA [12], sparse representation [13] and non-negative matrix factorization (NMF) [14] have been proposed. These methods aim at unknown image data estimation which is different from our application, but it can be easily found that the fundamental problem is the same, i.e., solving ill-posed problems.

Generally, many methods estimate unknown spectral reflectance by approximating it in lower-dimensional subspaces. Most of them are PCA-based methods and its improved versions [15]–[19]. Specifically, Agahian et al. enable the estimation of spectral reflectance based on weighted PCA which can adaptively determine the importance of each sample for the principal components [17]. In recent years, Nguyen et al. realize the estimation based on nonlinear mapping based on a radial basis function network [19]. In this method, they also perform the projection onto the subspace based on PCA. Furthermore, Abed et al. realize the spectral reflectance estimation by using an interpolation technique based on relationship between color values and the spectral reflectance [18]. In recent years, studies that focus on estimating spectral sensitivity of cameras [20]–[22] have also been carried out as similar studies in terms of the estimation of solutions for ill-posed problems.

In most methods which perform the approximation by low-dimensional subspaces obtained based on PCA and its variants, they realize the derivation of unique solutions for the ill-posed problems. Although PCA is the optimal multivariate analysis technique in terms of least-square approximation, it is also important to consider a unique characteristic of spectral reflectance. Thus, it can be expected that bases obtained on the basis of this characteristic improve the performance of the spectral reflectance estimation.

In this paper, we present a novel method for estimating spectral reflectance from image pairs including NIR components based on NMF [23]–[26]. The proposed method estimates spectral reflectance from only two kinds of input images: an image including both visible light components and NIR components and an image including only NIR components. These two images can be easily obtained by using a general digital camera without an IRCF and one with a visible light-cut filter, respectively. For example, a digital camera without an IRCF is used in several applications such as astronomical observation [27]. Furthermore, this camera can be implemented by removing IRCF from commercial digital cameras. The camera with a visible light-cut filter can be also implemented by using “the digital camera without an IRCF” with a commercial visible light-cut filter. In this way, since these two cameras can be implemented from commercial digital cameras by removing IRCF and using the commercial visible light-cut filter, we call them general digital cameras.

Since estimation of spectral reflectance from RGB values of the above two input images is generally an ill-posed problem, it is difficult to directly perform their estimation. Furthermore, RGB values are obtained from not only spectral reflectance but also the spectrum power distribution of the light source with the assumption that spectral sensitivity of the image sensor is known. In order to solve this problem, we use NMF for approximating the spectral reflectance, which has non-negative values, in lower-dimensional subspace to derive its solution. Furthermore, the proposed method realizes simple approximation of the spectrum power distribution of the light source with direct and scattered light components. Therefore, estimation of spectral reflectance becomes feasible in our method by using the spectrum power distribution of the light source. Consequently, from the estimated spectral reflectance, improvements of many fundamental applications can be realized. In this way, our method enables the estimation of both the spectral reflectance and the spectrum power distribution of the light source from only two kinds of images.

This paper is an extended version of [28]. Specifically, the proposed method newly introduces the following two points into our previously reported method [28]: 1) the estimation of the spectrum power distribution of the light source and 2) the use of bases obtained by applying NMF to a known spectral reflectance dataset.

This paper is organized as follows. First, Section II shows how RGB values are obtained from image sensors as preliminaries. Next, the NMF-based spectral reflectance estimation method is presented in Section III. In Section IV, we show some simulation results to verify the performance of the proposed method. In this section, the effectiveness of the proposed method is also shown by using the method in two applications, extraction of visible light components and detection of green plants, which can be realized from the estimated spectral reflectance. Finally, concluding remarks are given in Section V.

II. Preliminaries

This section shows an acquisition model of RGB values in general digital cameras. Image sensors inside digital cameras have different spectral sensitivities corresponding to the three colors, red (R), green (G) and blue (B). Each image is represented as a 1D array of pixels in scan line order. Furthermore, since each pixel value \( c_i \) (\( i = R, G, B \)) is independent from the other pixels, it can be obtained as follows:

\[
c_i = \int_{-\infty}^{\infty} s_i(\lambda)I_{\text{inc}}(\lambda) d\lambda = \int_{-\infty}^{\infty} s_i(\lambda)I_{\text{source}}(\lambda)r(\lambda) d\lambda, \tag{1}
\]

where \( \lambda \) represents the wavelength. Furthermore, \( s_i(\lambda) \) is a spectral sensitivity of the image sensor that corresponds to the \( i \) color component, \( I_{\text{inc}}(\lambda) \) is the spectrum power distribution of incident light, \( I_{\text{source}}(\lambda) \) is the spectrum power distribution of the light source and \( r(\lambda) \) is the spectral reflectance of the object being imaged.

By discretizing the wavelength, Eq. (1) is rewritten as
follows:

\[ c = S l_{\text{incident}} = S L_{\text{source}} r, \tag{2} \]

where \( c \in \mathbb{R}^3 \) is a column vector whose elements are RGB values, \( S \in \mathbb{R}^{3 \times d_i} \) is a matrix whose elements correspond to spectral sensitivities of the image sensor, \( l_{\text{incident}} \in \mathbb{R}^{d_i} \) is a column vector containing the spectrum power distribution of incident light, where \( d_i \) represents the number of partitions of the wavelength range. Furthermore, \( L_{\text{source}} \in \mathbb{R}^{d_i \times d_j} \) is a diagonal matrix whose diagonal elements are the spectrum power distribution of the light source, and \( r \in \mathbb{R}^{d_j} \) is a column vector whose elements correspond to the spectral reflectance. In the matrix \( S \), each row corresponds to a color channel \((R,G,B)\), and each column corresponds to a wavelength range. In addition, each diagonal element of the matrix \( L_{\text{source}} \) corresponds to a wavelength range. Each row of the column vectors \( l_{\text{incident}} \) and \( r \) also correspond to a wavelength range.

### III. NMF-based Spectral Reflectance Estimation

In this section, the spectral reflectance estimation method based on NMF is presented. In the proposed method, we try to estimate the spectral reflectance, i.e., \( r \) in Eq. (2), from RGB values, i.e., \( c \) in Eq. (2), of a pair of images. Specifically, these two images are an image including both visible light and NIR components (Visible-and-NIR image) and an image including only NIR components (NIR image). They can be easily obtained by using a general digital camera without an IRCF and one with a visible light-cut filter, respectively. In the proposed method, we estimate the spectral reflectance as well as the spectrum power distribution of the light source from the RGB values obtained from the above two images according to the known spectral sensitivity. It should be noted that estimation of both the spectral reflectance and spectrum power distribution of the light source is quite difficult. Therefore, the proposed method reformulates the target problem to a simpler problem to obtain its solution. Specifically, we represent the spectral reflectance and spectrum power distribution of the light source by simple linear combinations of some bases and try to estimate their linear coefficients. NMF is used for calculating these bases and their corresponding linear coefficients.

As mentioned above, we have to solve the ill-posed problem in order to realize the estimation of the spectral reflectance and the spectrum power distribution of the light source. Therefore, by approximating them in low-dimensional subspaces spanned by some bases, we try to find a solution to this problem. From this point of view, we use NMF for obtaining low-dimensional subspaces to estimate both the spectral reflectance and the spectrum power distribution of the light source from the ill-posed problem. It should be noted that spectrum data which are focused in this paper have non-negative values, and these data can be obtained by addition of several non-negative components not by their subtraction. Therefore, bases which span the subspaces and their corresponding coefficient values should be non-negative. Since NMF enables the low rank matrix decomposition into the non-negative basis matrix and coefficient matrix, we adopt NMF not the other multivariate analysis methods. We can see this good characteristic of NMF from Fig. 7 shown in the experiment. Although its detailed explanations are described in Section IV, we can see that all bases obtained by NMF become non-negative. This means NMF works better than the other multivariate analysis methods when targeting the estimation of the spectral reflectance and the spectrum power distribution of the light source which have the unique characteristic. Thus, the use of NMF is important for solving the ill-posed problem estimating the non-negative targets.

In this section, we show details of the problem reformulation in III-A. Next, the basis estimation based on NMF is presented in III-B. A spectral reflectance estimation algorithm that also includes estimation of the spectrum power distribution of the light source is presented in III-C.

#### A. Problem Reformulation

Problem reformulation in the proposed method is presented in this subsection. As stated above, it is difficult to directly estimate both the spectral reflectance \( r \) and the spectrum power distribution of the light source \( L_{\text{source}} \) in Eq. (2) from only the RGB values, \( c \). Therefore, as shown in Fig. 1, the proposed method represents these two components by linear combinations of several bases as follows:

\[ c_n \equiv S \left( a_n L_{\text{sun}} + (1 - a_n) L_{\text{sky}} \right) r_n \]

\[ \equiv S \left( a_n L_{\text{sun}} + (1 - a_n) L_{\text{sky}} \right) \hat{R}^b r_n^w, \tag{3} \]

where \( n = 1, 2, \ldots, N \) represents the \( n \)-th pixel in the target images, and \( N \) is the total number of pixels. The above equation can be obtained by the following approximations:

\[ L_{\text{source}} \equiv \alpha L_{\text{sun}} + (1 - \alpha) L_{\text{sky}}, \tag{4} \]

\[ r_n \equiv \hat{R}^b r_n^w. \tag{5} \]

The details of each symbol in Eq. (3) are shown below. In the proposed method, spectral reflectance is estimated from two input images of the same dimensions: a Visible-and-NIR image and an NIR image. Let \( c_n \in \mathbb{R}^6 \) be a column vector that contains RGB values of the \( n \)-th pixel from the two input images, and let \( r_n \in \mathbb{R}^{d_i} \) be a column vector containing spectral reflectance of the \( n \)-th pixel. Then these two vectors \( c_n \) and \( r_n \) are respectively defined by

\[ c_n = \begin{bmatrix} c_{nR}^+, c_{nG}^+, c_{nB}^+, c_{nR}^-, c_{nG}^-, c_{nB}^- \end{bmatrix}^T, \tag{6} \]

\[ r_n = \begin{bmatrix} r_{n1} & r_{n2} & \cdots & r_{nd} \end{bmatrix}^T, \tag{7} \]

where \( c_{ni}^+ (i \in \{R,G,B\}) \) is the \( n \)-th pixel value of the Visible-and-NIR image, \( c_{ni}^- \) is the \( n \)-th pixel value of the NIR image, and \( r_{nj} \) corresponds to the \( j \)-th wavelength range of the spectral reflectance of the object. Furthermore, in Eq. (3), the matrix \( S \in \mathbb{R}^{3 \times d_i} \) respectively containing the spectral sensitivities of
the unfiltered camera and the NIR camera is defined as

\[
S = \begin{bmatrix}
s^+_R & s^+_G & \cdots & s^+_B \\
s^+_R & s^+_G & \cdots & s^+_B \\
\vdots & \vdots & \ddots & \vdots \\
s^+_R & s^+_G & \cdots & s^+_B
\end{bmatrix},
\]

(8)

where \(s^+_{ij} (i \in \{R, G, B\})\) corresponds to the spectral sensitivity of the unfiltered camera in the \(j\)-th wavelength range and \(s^-_{ij}\) corresponds to the spectral sensitivity of the NIR camera in the \(j\)-th wavelength range. Each row of \(S\) corresponds to a color component, and each column of \(S\) corresponds to a wavelength range. As described above, it is assumed here that \(S\) is known. In addition, the diagonal matrices \(L_{sun} \in \mathbb{R}^{d_L \times d_L}\) and \(L_{sky} \in \mathbb{R}^{d_L \times d_L}\) contain the spectrum power distributions of direct and scattered light components, respectively, and \(0 \leq \alpha_n \leq 1\) is a parameter of the \(n\)-th pixel that determines the balance between these two distributions. If light conditions are known, these spectrum power distributions can also be obtained. Therefore, we assume that these two distributions \(L_{sun}\) and \(L_{sky}\) can be provided. Next, in Eq. (3), \(\hat{R}^b \in \mathbb{R}^{d_L \times d_L}\) is a non-negative basis matrix obtained by NMF in the following subsection, where \(d_r(\leq d_L)\) is a dimension of the space spanned by these bases. Then \(\hat{r}^b_n \in \mathbb{R}^{d_r}\) is its corresponding non-negative coefficient vector. As shown in Eq. (3), the proposed method reformulates the problem of estimating \(L_{source}\) and \(r_n\) into the problem of estimating \(\alpha_n\) and \(r^b_n\). Therefore, we only have to perform estimation of a small number of elements by this reformulation.

As shown in Eq. (4), we separate the light source as direct and scattered light components. In the proposed method, we have to estimate both the spectral reflectance and the spectrum power distribution of the light source from only six pixel values (“three RGB values of a Visible-and-NIR image” and “three RGB values of an NIR image”). Therefore, this problem is an ill-posed problem. In order to find a solution to this problem, we introduce lower-dimensional approximation of the spectral reflectance and the spectrum power distribution of the light source. For the spectral reflectance, we prepare training dataset and calculate NMF-based bases which span the low-dimensional subspace. On the other hand, for the spectrum power distribution of the light source, we adopt the approximation by using the subspace, whose bases correspond to the direct and scattered light components. Therefore, in order to find a solution to the above ill-posed problem, we have to perform the approximation of the spectrum power distribution of the light source in the subspace spanned by a quite limited number of bases. This is the motivation of the approximation of the spectrum power distribution of the light source.

Furthermore, we assume that the Visible-and-NIR image and the NIR image are taken in the daytime. Rüfenacht et al. have found that images taken in the daytime can be divided to direct light regions and shadow regions as shown in [29]. In this work, the light of the direct light regions is composed of the direct and scattered light components, and that of the shadow regions is composed only of the scattered light component as shown in Fig. 2. Therefore, according to the idea of their work, we prepare two bases corresponding to the direct and scattered light components and perform the approximation of the spectrum power distribution of the light source in this low-dimensional subspace. From the above reason, we separate the light source as direct and scattered light components and model it by using Eq. (4).

Note that as shown in the approximation of the spectrum power distribution of the light source by Eq. (4), its maximum value is determined. Therefore, if the true maximum value of the spectrum power distribution of the light source becomes larger or smaller than this maximum value, the whole estimated spectrum power distribution of the light source should be multiplied by a constant. However, as mentioned above, since the maximum value of the spectrum power distribution of the light source is fixed by the approximation in Eq. (4), this cannot be represented. This means that Eq. (4) only determines the mixture ratio of the spectrum power distributions of direct and scattered light components, and the power of the light source cannot be determined by this equation. Instead, the estimated spectral reflectance becomes a constant multiple of the true spectral reflectance in our method. Therefore, the spectral reflectance estimation by our method can represent relative power of each wavelength but not its absolute power.

Given a Visible-and-NIR image and an NIR image including \(N\) pixels, their matrices containing RGB values and the spectral reflectance are respectively defined as follows:

\[
C = [c_1, c_2, \ldots, c_N],
\]

(9)

\[
R = [r_1, r_2, \ldots, r_N].
\]

(10)
which satisfy the Hadamard product, and \( \alpha \) are all one, respectively, where \( A \) is a matrix including the non-negative elements. Regions including both direct and scattered light components, and that of the shadow regions is composed of the direct and scattered light components, and that of the shadow regions is composed only of the scattered light component.

Fig. 2. The proposed model of the light source. The light of the direct light regions is composed of the direct and scattered light components, and that of the shadow regions is composed only of the scattered light component.

Therefore, Eq. (3) can be rewritten as

\[
C \in \{ L_{sun} \mathbf{I}_{d \times N} + L_{sky} \mathbf{I}_{d \times N} (\mathbf{I}_{N \times N} - A) \} \circ \mathbf{R}
\]

\[
\approx \{ [L_{sun} \mathbf{I}_{d \times N} + L_{sky} \mathbf{I}_{d \times N} (\mathbf{I}_{N \times N} - A)] \circ (\hat{\mathbf{R}}^e \mathbf{R}^w) \} \quad (11)
\]

where \( A \in \mathbb{R}^{N \times N} \) is a diagonal matrix whose diagonal elements are \( a_n \ (n = 1, 2, \cdots, N) \), \( \mathbf{I}_{d \times b} \) is an \( a \times b \) matrix whose elements are all one, \( \mathbf{I}_{a \times b} \) is the \( a \times b \) identity matrix, \( \circ \) represents the Hadamard product, and

\[
\mathbf{R}^w = \left[ r_1^w, r_2^w, \ldots, r_N^w \right] \quad (12)
\]

is a matrix including the non-negative coefficients \( r_n^w \) \((n = 1, 2, \cdots, N)\) in each column. In Eq. (11), \( \mathbf{R} \equiv \hat{\mathbf{R}}^e \mathbf{R}^w \).

From Eq. (11), given a Visible-and-NIR image and an NIR image, i.e., the matrix \( C \), the proposed method tries to estimate \( A \) \((\alpha_n \ (n = 1, 2, \cdots, N))\) and \( \mathbf{R}^w \ (r_n^w \ (n = 1, 2, \cdots, N)) \) from the known matrices \( S, L_{sun} \) and \( L_{sky} \). Note that for performing this estimation, we have to previously obtain the basis matrix \( \hat{\mathbf{R}}^e \). This matrix is calculated from a known training spectral reflectance dataset in the proposed method. Thus, in the following subsection, we first show the basis matrix estimation and next explain the details of its algorithm.

**B. Basis Estimation Based on NMF**

This subsection shows the method for estimation of the basis matrix \( \hat{\mathbf{R}}^e \) from a known dataset of spectral reflectance. In the proposed method, we prepare a dataset of known spectral reflectance and define a matrix \( \hat{\mathbf{R}} \in \mathbb{R}^{d \times M} \) that contains \( \hat{r}_m \in \mathbb{R}^{d_i} \ (m = 1, 2, \cdots, M) \) in each column, where \( M \) is the number of training examples. From a characteristic that all elements in \( \hat{\mathbf{R}} \) are non-negative values, we calculate the basis matrix based on NMF [23]. NMF enables the decomposition of \( \hat{\mathbf{R}} \) into a non-negative basis matrix \( \hat{\mathbf{R}}^e \in \mathbb{R}^{d \times d} \) and its corresponding non-negative coefficient matrix \( \hat{\mathbf{R}}^w \in \mathbb{R}^{d \times M} \) which satisfy \( \hat{\mathbf{R}} \approx \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w \).

According to [24], the proposed method estimates \( \hat{\mathbf{R}}^e \) and \( \hat{\mathbf{R}}^w \) from \( \hat{\mathbf{R}} \) by minimizing

\[
\| \hat{\mathbf{R}} - \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w \|_F^2 = \sum_{j=1}^{d_i} \sum_{m=1}^{M} \left( (\hat{\mathbf{R}} - \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w)_{j m} \right)^2,
\]

where \( \| \cdot \|_F \) is the Frobenius norm and \((\cdot)_{j m}\) represents the \((j, m)\)-th element of a target matrix. The minimization of Eq. (13) yields the following iterative update rules:

\[
\left( \hat{\mathbf{R}}^e \right)_{\mu \beta} \leftarrow \left( \hat{\mathbf{R}}^e \right)_{\mu \beta} \left( \hat{\mathbf{R}}^e \right)^T_{\mu \beta} \left( \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w \right)^T_{\mu \beta}, \forall \mu, \beta,
\]

\[
\left( \hat{\mathbf{R}}^w \right)_{\gamma \mu} \leftarrow \left( \hat{\mathbf{R}}^w \right)_{\gamma \mu} \left( \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w \right)^T_{\gamma \mu}, \forall \gamma, \mu.
\]

The least-squares cost function is non-increasing under the condition of these update rules [24].

In this way, the proposed method enables estimation of the non-negative basis matrix \( \hat{\mathbf{R}}^e \) from the known dataset. It should be noted that many improved versions in the field of NMF have been proposed, and the above algorithm is one of the simplest approaches [25]. It is well known that when NMF is adopted, we have to select the optimal divergence for obtaining results of the low rank matrix decomposition. In this paper, we select the Euclidean distance shown in Eq. (13) for its simplicity. There have been proposed various divergences for NMF. For example, if we adopt the well known I-divergence, we have to estimate the optimal matrices \( \hat{\mathbf{R}}^e \) and \( \hat{\mathbf{R}}^w \) from \( \hat{\mathbf{R}} \) minimizing

\[
D_I(\hat{\mathbf{R}} || \hat{\mathbf{R}}^e \hat{\mathbf{R}}^w) = \sum_{j=1}^{d_i} \sum_{m=1}^{M} \left( (\hat{\mathbf{R}})_{j m} \ln \left( (\hat{\mathbf{R}}^e \hat{\mathbf{R}}^w)_{j m} \right) \right) - \left( (\hat{\mathbf{R}})_{j m} + (\hat{\mathbf{R}}^e \hat{\mathbf{R}}^w)_{j m} \right)
\]

instead of using Eq. (13). Naturally, if the divergence changes, the optimization algorithm for minimizing it also changes, i.e., we have to adopt the algorithm which is designed for each selected divergence and different from that shown in Eqs. (14) and (15). As reported in [26], the selection of the optimal divergence among various divergences is an important problem. This strongly depends on the nature of the target data to be analyzed. Furthermore, some divergences include parameters, and there exists trade-off when adjusting the parameters, e.g. trade-off between robustness and efficient estimation. Fortunately, since the Euclidean distance adopted in the proposed method does not include any parameters, we do not have to consider this trade-off.

As described above, when the target spectral reflectance and spectrum power distribution of the light source are suitable for the Euclidean distance shown in Eq. (13), NMF adopting this distance works, effectively. On the other hand, when other divergences are suitable for our estimation problem, it may become difficult for our method to find satisfactory results. In such a case, we should adopt different divergences in our NMF-based algorithm, but this is only the modification of divergences used for NMF, the fundamental algorithm of the proposed method is the same. Nevertheless, since this is not the main focus of this paper, we adopt the above algorithm using the Euclidean distance.

**C. Spectral Reflectance Estimation Algorithm**

This subsection shows the algorithm for estimating spectral reflectance with the spectrum power distribution of the light
source. As described above, the proposed method tries to estimate $\alpha_n$ and $r_n^w$ $(n = 1, 2, \cdots, N)$ instead of directly estimating $L_{\text{source}}$ and $r_n$ $(n = 1, 2, \cdots, N)$. Specifically, $\alpha_n$ is first estimated and then $r_n$ is estimated by using the estimation result of $\alpha_n$. The details are shown below.

1) Estimation of Parameter $\alpha_n$

In the proposed method, $\alpha_n$ is estimated on the basis of the relationship between its value and the spectrum power distribution of incident light. An overview of the procedures is shown in Fig. 3. In order to obtain the relationship, the proposed method prepares pairs of $\hat{\alpha}_k$ and $\hat{L}_{\text{incident}}(k) \in \mathbb{R}^{d_k}$ $(k = 1, 2, \cdots, K)$, where $K$ is the number of training samples. From several samples of $L_{\text{source}}$ determined by $\alpha$ in Eq. (4) and the training spectral reflectance of $r$, the samples $\hat{L}_{\text{incident}}(k)$ can be obtained (Step 1 in Fig. 3). Specifically, since $\alpha$ is changed as $0.0, 0.1, \cdots, 1.0$ and $M$ training spectral reflectance data in the previous subsection are used, $11M$ training samples of the spectrum power distribution of incident light are totally obtained, i.e., $K = 11M$. Then the following decomposition is performed:

$$
\hat{L}_{\text{incident}} \approx \hat{L}_{\text{incident}}^b \hat{L}_{\text{incident}}^w
$$

(17)

where $\hat{L}_{\text{incident}} = [\hat{L}_{\text{incident}}(1), \hat{L}_{\text{incident}}(2), \cdots, \hat{L}_{\text{incident}}(K)] \in \mathbb{R}^{d_t \times K}$, and $\hat{L}_{\text{incident}}^b \in \mathbb{R}^{d_t \times d_t}$ and $\hat{L}_{\text{incident}}^w \in \mathbb{R}^{d_t \times K}$ are respectively non-negative basis and coefficient matrices. Note that $d_t$ is a predefined dimension. The proposed method calculates $\hat{L}_{\text{incident}}^b$ and $\hat{L}_{\text{incident}}^w$ based on NMF (Step 2 in Fig. 3).

Furthermore, in our method, we focus on the relationship between the obtained coefficient matrix $\hat{L}_{\text{incident}}^w$ and $\hat{\alpha} = [\hat{\alpha}_1, \hat{\alpha}_2, \cdots, \hat{\alpha}_K]^T$. Specifically, the following regression problem is solved:

$$
(\hat{L}_{\text{incident}}^w)^T v = \hat{\alpha}.
$$

(18)

The optimal solution $v \in \mathbb{R}^{d_t}$ is easily obtained as

$$
v = (\hat{L}_{\text{incident}}^w (\hat{L}_{\text{incident}}^w)^T)^{-1} \hat{L}_{\text{incident}}^w \hat{\alpha}.
$$

(19)

In this way, the proposed method enables estimation of the relationship between $\hat{\alpha}_k$ and the spectral power distribution of incident light (the column vectors of $\hat{L}_{\text{incident}}^w$) by calculating $v$ in Eq. (19) (Step 3 in Fig. 3). Therefore, given $c_n$ for each $n$-th pixel of the target images, its coefficient vector $l_{\text{incident}}^w(n)$ satisfying

$$
c_n = S \hat{L}_{\text{incident}}^b l_{\text{incident}}^w(n) = Ql_{\text{incident}}^w(n)
$$

(20)

is obtained for each element $\mu$ as follows:

$$
l_{\text{incident}}^w(n)_\mu = (Q^T c_n)_\mu (Q^T (l_{\text{incident}}^w(n))_\mu) \quad \forall \mu,
$$

(21)

where $Q = S\hat{L}_{\text{incident}}^b$. Therefore, $\alpha_n$ can be estimated by the following equation:

$$
\alpha_n = v^T l_{\text{incident}}^w(n).
$$

(22)

In this way, the estimation of $\alpha_n$ $(n = 1, 2, \cdots, N)$ becomes feasible by focusing on the relationship between its value and the spectrum power distribution of incident light (Step 4 in Fig. 3). Since the spectrum power distribution of the light source and the spectral reflectance are generally independent, it is not suitable to obtain their relationship. Thus, our method estimates the relationship between $\alpha_n$ and the spectrum power distribution of incident light. Furthermore, if the dimension of the spectrum power distribution of incident light $d_t$ becomes larger, it also becomes difficult to obtain the relationship, i.e., the estimation of $v$ becomes difficult. Therefore, we reduce its dimension based on NMF and calculate the relationship between $l_{\text{incident}}^w(n)$ and $\hat{\alpha}_k$ $(k = 1, 2, \cdots, K)$. Then, as shown in Eq. (19), we estimate the solution of the regression problem, and the input is the coefficient matrix $l_{\text{incident}}^w$ not its original matrix $L_{\text{incident}}$. We show an example figure in Fig. 4. This figure shows the relationship between the true value of $\alpha_n$ and its estimation result by Eq. (22) when we use $L_{\text{incident}}^w$ and $L_{\text{incident}}$ in Eq. (19). In this example, we change the true value of $\alpha_n$ to 0.0, 0.1, \cdots, 1.0. From this figure, it can be seen that when simply using $L_{\text{incident}}^w$, the estimation results are scattered, and the estimation performance tends to become worse. Therefore, we can see that the use of $L_{\text{incident}}$ outputs better results. The experiment shown here is the same as that shown in the following example section, and its details are described below.

2) Estimation of Coefficient Vector $r_n^w$

The proposed method tries to estimate $r_n^w$ $(n = 1, 2, \cdots, N)$ from the estimated values of $\alpha_n$ $(n = 1, 2, \cdots, N)$. In order to estimate $r_n^w$ $(n = 1, 2, \cdots, N)$, we rewrite Eq. (3) as

$$
c_n = P_{\alpha_n} r_n^w,
$$

(23)
where

\[ P_{\alpha_n} = S \left[ \alpha_n L_{\text{sun}} + (1 - \alpha_n) L_{\text{sky}} \right] \tilde{R}^b. \]  

(24)

Then, from the non-negative matrices \( C \) in Eq. (9) and \( P_{\alpha_n} \), we estimate \( R^w \) including \( r_n^w \) \((n = 1, 2, \ldots, N)\) which minimize

\[
E(R^w) = \left\| C - P_{\alpha_n} R^w \right\|_F^2 = \sum_{n=1}^{N} \left\| c_n - P_{\alpha_n} r_n^w \right\|_F^2. \]

(25)

Thus, in the same manner as shown in the previous subsection, we estimate \( r_n^w \) \((n = 1, 2, \ldots, N)\) by the following update rule:

\[
(r_n^w)_\mu \leftarrow \frac{(P_{\alpha_n} c_n)_\mu}{(P_{\alpha_n}^T P_{\alpha_n})_\mu}, \quad \forall \mu. \]

(26)

Then, by iteratively updating \( r_n^w \) based on the above rule, we can estimate the spectral reflectance \( r_n = \tilde{R}^b r_n^w \) \((n = 1, 2, \ldots, N)\) of each pixel \( n \).

As described above, the proposed method estimates spectral reflectance by estimating the corresponding coefficient vectors \( r_n^w \). This means that spectral reflectance is estimated in the lower-dimensional subspace spanned by the bases, i.e., the column vectors in \( \tilde{R}^b \). Compared to the problem of directly estimating the \( d_1 \)-dimensional spectral reflectance vector, the problem of estimating the \( d_r \)-dimensional \((d_r \leq d_1)\) vector becomes easier for obtaining the solutions. Furthermore, we also estimate the combination parameter \( \alpha_n \) which determines the balance between the spectrum power distributions of direct and scattered light components. Naturally, it is difficult to estimate the whole spectrum power distribution of the light source \( L_{\text{source}} \) with the spectral reflectance. Therefore, the proposed method also approximates the distribution of light source at each pixel \( n \) by only one parameter \( \alpha_n \). Consequently, since the number of the estimation targets becomes smaller, we can find the solution of the problem.

IV. EXPERIMENTAL RESULTS

In order to verify the performance of the proposed method, we show some experimental results in this section. We verified the estimation performance by the following two approaches. First, we performed estimation of spectral reflectance from simulation data for which spectral reflectance is known. Then we compared the estimated spectral reflectance and the ground truth for verifying the performance of our method (See IV-A). Next, we performed evaluation of the proposed method by using real images. Since the true spectral reflectance in those real images cannot be known, we used the estimated spectral reflectance for two applications, extraction of visible light components and detection of green plants. Then, from the obtained results, we verified the performance of the proposed method (See IV-B).

A. Performance Verification Based on Simulation Results

This subsection shows verification of the performance of spectral reflectance estimation from simulation results. Since the spectral reflectance cannot be known from real images, we prepared simulation data and applied the proposed method to these data for evaluating the performance of the proposed method. In this experiment, we used 1327 samples, for which spectral reflectance was in the range of 400nm–1100nm, selected from ASTER SPECTRAL LIBRARY [30]. By using this dataset, we performed performance verification by dividing the dataset into two groups corresponding to the training data (664 samples) and test data (663 samples). Then we randomly performed this selection five times and output their average performance. According to the simple model of Eq. (3), we changed the parameter \( \alpha_n \) as 0.0, 0.1, 0.2, \ldots, 1.0, and 663 \times 11 = 7293 color values, i.e., 7293 patterns of \( c_n \), were generated. From these randomly generated test data, we performed spectral reflectance estimation. In this experiment, \( d_1 = 701, N = 7293, M = 664 \) and \( K = 7304 \). Furthermore, we assumed that the spectral sensitivity \( S \) was known and it was set as shown in Fig. 5, and the spectrum power distributions of direct and scattered light components, i.e., the diagonal elements of \( L_{\text{sun}} \) and \( L_{\text{sky}} \), were provided as shown in Fig. 6.

For comparison, we used the following three comparative methods.

i) Comparative method 1:
This method does not use the basis estimation based on NMF. This method was used for verifying the novel approach of our method, i.e., bases obtained by NMF being used for spectral reflectance estimation.

ii) Comparative method 2:
This method uses basis estimation based on NMF but
of the spectral reflectance estimation, we adopted this measure most commonly used measure for the performance verification. Histogram intersection becomes larger.

Figure 7 shows the estimated bases obtained by the proposed method. In this figure, we change the dimension $d_r$ of the low-dimensional subspace spanned by the bases of $\hat{R}^b$ as 2, 4, 6, 8 and show these bases for each condition. From the obtained results, we can see that bases that can cover the whole wavelengths are obtained. Next, Fig. 8 shows the results of estimation of spectral reflectance by the proposed method and the comparative methods. As mentioned in III-A, the amplitude of the spectral reflectance depends on the power of the light source in our method. Therefore, if the power of the light source becomes smaller, its amplitude also becomes smaller as shown in Fig. 8. Therefore, the spectral reflectance estimated by the proposed method corresponds to the estimate of a constant multiple of the true spectral reflectance. In quantitative evaluation shown below, we performed its normalization in such a way that the sum of the spectral reflectance becomes one.

From these results, it can be seen that the proposed method enables successful estimation. In order to make the difference of the performance clearer, we also show root mean squared error (RMSE) and normalized histogram intersection of the estimated spectral reflectance obtained from the test data in Table I. RMSE and normalized histogram intersections are obtained by comparing the estimated result and the ground truth. Then, if the performance of one method is better than the other methods, its RMSE becomes smaller and its histogram intersection becomes larger. Since RMSE is the most commonly used measure for the performance verification of the spectral reflectance estimation, we adopted this measure in the quantitative evaluation. Furthermore, the histogram intersection is commonly used for monitoring similarity between two distributions. As shown in the application of the proposed method, i.e., the detection of green plants, which is explained in the following subsection, accurate estimation of the distribution of the spectral reflectance is very important for guaranteeing its performance. Therefore, in order to confirm the similarity of the distributions between the estimation result and the ground truth, we adopted the histogram intersection.

In addition to the above comparative methods, we performed the comparison with the following state-of-the-art methods: PCA-based method, the methods in [17], [18] and [19]. The method in [19] is the most state-of-the-art method. Furthermore, in [19], they performed the comparison with the PCA-based method and the methods proposed in [17] and [18] as the state-of-the-art methods. Therefore, we also performed the comparison between the proposed method and the above four methods. In this experiment, we implemented the PCA-based method, the methods in [17], [18] and [19] by using C++\(^1\).

As shown in this quantitative comparison, the proposed method outputs better spectral reflectance estimation results than those of the comparative methods, and its performance tends to be the best when $d_r = 6$. In addition, we show quantitative evaluation results of the estimated spectrum power distributions of the light source in Table II. In this table, we show the RMSE of the estimated spectrum power distributions of the light source and that of $\alpha_n$. Furthermore, the normalized histogram intersection between the estimated spectrum power distributions of the light source and the ground truth is also shown. Note that the results obtained by our method and comparative method 1 are the same since their approaches for estimation of $\alpha_n$ are the same. Similarly, the results of comparative methods 2 and 3 are the same. By comparing the

\(^1\) Since Matlab source codes were published in [19], we performed the implementation of the method in [19] using C++ according to these Matlab source codes for reducing the computation time. Therefore, we could confirm that the same performance can be obtained by using both Matlab version of [19] and C++ version of our implementation.
TABLE I

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>Histogram Intersection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method (d₁ = 2)</td>
<td>2.876 × 10⁻⁴</td>
<td>0.9560</td>
</tr>
<tr>
<td>Proposed method (d₁ = 4)</td>
<td>2.463 × 10⁻⁴</td>
<td>0.9648</td>
</tr>
<tr>
<td>Proposed method (d₁ = 6)</td>
<td>2.408 × 10⁻⁴</td>
<td>0.9654</td>
</tr>
<tr>
<td>Proposed method (d₁ = 8)</td>
<td>2.419 × 10⁻⁴</td>
<td>0.9668</td>
</tr>
<tr>
<td>Comparative method 1</td>
<td>5.451 × 10⁻⁴</td>
<td>0.9255</td>
</tr>
<tr>
<td>Comparative method 2</td>
<td>2.565 × 10⁻⁴</td>
<td>0.9646</td>
</tr>
<tr>
<td>Comparative method 3</td>
<td>5.645 × 10⁻⁴</td>
<td>0.9146</td>
</tr>
<tr>
<td>PCA-based method</td>
<td>9.162 × 10⁻⁴</td>
<td>0.8001</td>
</tr>
<tr>
<td>Reference [17]</td>
<td>6.453 × 10⁻⁵</td>
<td>0.8513</td>
</tr>
<tr>
<td>Reference [18]</td>
<td>5.104 × 10⁻⁴</td>
<td>0.9216</td>
</tr>
<tr>
<td>Reference [19]</td>
<td>3.493 × 10⁻⁴</td>
<td>0.9184</td>
</tr>
</tbody>
</table>

In this experiment, we set d₁ = 6.

results of our method and the comparative methods, it can be seen that the estimation algorithm in the proposed method is effective, and its performance tends to be the best when d₁ = 6.

As shown in the above experimental results, the proposed method outperforms the comparative methods. Even if we adopt a sophisticated model representing the acquisition model of RGB values in general digital cameras, the number of estimation targets becomes larger, and it becomes difficult to estimate all of them as shown in the results of comparative methods 1 and 3. In order to solve this problem, the proposed method adopts NMF and reduces the number of estimation targets by approximating the spectral reflectance in the low-dimensional subspace spanned by the non-negative bases. In addition, the effectiveness of estimation of the spectrum power distribution of the light source can be seen from the results of comparative methods 2 and 3.

Furthermore, we compared the computation times of the proposed method and the comparative methods. The experiments were performed on a personal computer using Intel(R) Core(TM) i7-3930K CPU 3.20 GHz with 32.4 Gbytes RAM. The implementation was performed by using C++. The average computation times of the proposed method and comparative methods 1–3 are about 21.6 sec, 2.64 × 10³ sec, 17.1 sec and 2.64 × 10³ sec, respectively. Therefore, the proposed method enables faster computation than comparative methods 1 and 3. Since the proposed method reduces the dimension of the spectral reflectance, faster estimation becomes possible compared to the methods directly estimating higher-dimensional spectral reflectance. On the other hand, the computation times of the PCA-based method and the methods in [17], [18], [19] are 9.13 sec, 4.73 × 10³ sec, 1.65 sec and 1.03 × 10² sec, respectively. Thus, some approaches for reducing the computation cost are still necessary in our method.

B. Application of Spectral Reflectance Estimation

This subsection shows results obtained by using the proposed method for two applications, extraction of visible light components and detection of green plants. In these experiments, we estimated spectral reflectance from a pair of target images, a Visible-and-NIR image and an NIR image, and applied the obtained results to these applications for verifying the performance of our method.

First, we explain the experimental conditions. In the experiments, the input image pairs were obtained under natural sunlight, and their size was 818×600 pixels, i.e., N = 490800. We show the details about the camera used in the experiment, the lenses and the filters, visible light-cut filter and IRCF respectively used for obtaining NIR images and ground truth images including only visible light components. Specifically, we used the following equipments: Camera: Sony, ICX274, Lens: SPACECOM, HD880MIR, Visible light-cut filter: FUJIFILM, SC70 and IRCF: Kenko, DR655. The input image pairs, Visible-and-NIR images taken by the unfiltered camera and NIR images taken by the NIR camera, are shown in Fig. 9. These input images are 24 bit color. We call these two images shown in Fig. 9 test images 1 and 2, respectively. In these experiments, d₁ was simply set to six, and the wavelength ranging from 475nm to 925nm was divided into six sub-ranges: 475nm – 550nm, 550nm – 625nm, 625nm – 700nm, 700nm – 775nm, 775nm – 850nm and 850nm – 925nm. In the proposed method, we used the bases for reducing the number of estimation targets. Unfortunately, since it is difficult to prepare versatile training dataset in [30] for obtaining the suitable bases, we reduced the dimension of the wavelength d₁. Furthermore,

We performed the experiments under the above-described conditions. The experimental results of extraction of visible light components and detection of green plants are shown below.

1) Extraction of Visible Light Components: In this experiment, we applied the obtained results to these applications. Let \( \bar{S} \in \mathbb{R}^{36} \) be the matrix that corresponds to the spectral sensitivity of a digital camera with an IRCF. Then, according to Eq. (3), an RGB value vector \( \bar{c}_n \in \mathbb{R}^3 \) including only the
visible light components at each pixel \( n (n = 1, 2, \cdots, N) \) can be obtained as follows:

\[
\tilde{c}_n = \tilde{S} \left( \alpha_n L_{\text{sum}} + (1 - \alpha_n) L_{\text{sky}} \right) \tilde{R}^b \tilde{p}_n^v.
\]

Thus, the matrix \( \tilde{C} = [\tilde{c}_1, \tilde{c}_2, \cdots, \tilde{c}_N] \) including the whole pixel values of visible light components is obtained as

\[
\tilde{C} = \tilde{S} \left[ \left[ L_{\text{sum}} I_{d_i,N} A + L_{\text{sky}} I_{d_i,N} (I_{N,N} - A) \right] \circ \left( \tilde{R}^b R^v \right) \right] \quad (31)
\]

according to Eq. (11). In the matrix \( \tilde{S} \), each row corresponds to a color channel \( (R, G, B) \) and each column corresponds to a wavelength range. Specifically, in this experiment, \( \tilde{S} \) is defined as

\[
\tilde{S} = \left( \begin{array}{cccc}
0 & 2.0 & 4.4 & 0.4 & 0 & 0 \\
0.8 & 4.6 & 1.6 & 0.2 & 0 & 0 \\
3.8 & 1.4 & 0.2 & 0 & 0 & 0
\end{array} \right). \quad \quad (32)
\]

By using Eq. (31), an image including only visible light components is obtained.

Figure 10 shows the results obtained by our method and the following comparative method.

iv) Comparative method [4]:

In reference [4], the pixel value \( c_{i}^{\text{comp}} (i \in \{R, G, B\}) \) is calculated as follows:

\[
c_{i}^{\text{comp}} = c_{i}^{+} - K_i c_{i}^{-}, \quad (33)
\]

where \( c_{i}^{+} \) is the pixel value of the input Visible-and-NIR image, \( c_{i}^{-} \) is the pixel value of the input NIR image, and \( K_i \) is a weighting coefficient. The coefficient \( K_i \) was adjusted to maximize the histogram intersection between the comparative image and the ground truth image.

In addition, extraction results of the visible light components obtained by our method for six other images are shown in Fig. 11 (test images 3, 4 and 5) and Figs. 13(a)–(c) (test images 6, 7 and 8).

In order to verify the performance of the proposed method quantitatively, we evaluated the visible light component extraction results by comparing with images including only visible light components taken by a digital camera with an IRFCF (ground truth images) through normalized histogram intersection values. For test images 1 and 2, the ground truth images including only visible light components correspond to Figs. 10(a) and (b), respectively. Furthermore, those of test images 3–5 are Figs. 11(a)–(c), respectively. The histogram intersection values indicate the color similarity between two images, and a large histogram intersection value corresponds...
to a good result. The results obtained by using our method and the comparative method [4] are shown in Table III. In order to ignore small differences in color, the number of colors is reduced from 16,777,216 to 64. According to Table III, most extraction results by our method have colors that are more similar to those of the ground truth images than those of the comparative methods. It should be noted that in test image 8 (Fig. 13(c)), the histogram intersection of our method and the comparative method [4] are shown in Table III. In this method, we perform a simple thresholding of the IR images as the comparison of our method in Figs. 12 and 13. In this method, we perform a simple thresholding of the total power of the NIR components. From the obtained results, it can be seen that not only the green plants but also other different objects are also detected. This is because these objects have similar characteristics in the NIR range. From the above three conditions, we need to monitor the visible light range (Condition 1) and the relationship between the NIR range and visible light range (Conditions 2 and 3) for detecting only green plants. Therefore, if we only use the IR images, other objects different from green plants are also detected.

Interestingly, by using the estimated spectral reflectance and the detection results of green plants, we can perform object-based color transformation. Figure 14 shows examples that simulate the autumn color of green plants. For the pixels detected as green plants, we multiplied the spectral reflectance in the NIR range by a factor of 1.5 and that in the visible light range by a factor of 0.95. The histograms of the test images are normalized by their total power.

### Table III

<table>
<thead>
<tr>
<th>Image</th>
<th>Proposed Method</th>
<th>Reference [4]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test image 1</td>
<td>0.8741</td>
<td>0.6982</td>
</tr>
<tr>
<td>Test image 2</td>
<td>0.8250</td>
<td>0.7366</td>
</tr>
<tr>
<td>Test image 3</td>
<td>0.8470</td>
<td>0.7273</td>
</tr>
<tr>
<td>Test image 4</td>
<td>0.8990</td>
<td>0.8648</td>
</tr>
<tr>
<td>Test image 5</td>
<td>0.8828</td>
<td>0.8651</td>
</tr>
<tr>
<td>Test image 6</td>
<td>0.8513</td>
<td>0.8242</td>
</tr>
<tr>
<td>Test image 7</td>
<td>0.9231</td>
<td>0.9114</td>
</tr>
<tr>
<td>Test image 8</td>
<td>0.6932</td>
<td>0.7816</td>
</tr>
</tbody>
</table>

Fig. 10. Experimental results of visible light component extraction: (a), (b) ground truth images including only visible light components taken by the digital camera with an IRCF, (c), (d) results of extraction by the proposed method, (e), (f) results of extraction by comparative method [4].

2) Detection of Green Plants: As described above, it was confirmed that the proposed method realizes accurate spectral reflectance estimation, and this enables performance improvement of applications related to color corrections. Here, we show another application, detection of green plants using spectral reflectance estimated by the proposed method. Green plants have the following characteristics: the spectral reflectance peak is around the wavelength of 550 nm, and the reflectance peak is around the wavelength of 625 nm.
Fig. 11. Other experimental results of visible light component extraction: (a)–(c) ground truth images including only visible light components taken by the digital camera with an IRCF, (d)–(f) visible light component extraction results by our method, (g)–(i) visible light component extraction results by comparative method [4].

Fig. 12. Experimental results of green plant detection: (a) result obtained from input images shown in Figs. 9(a) and (c), (b) result obtained from input images shown in Figs. 9(b) and (d). Furthermore, (c) and (d) show green plant detection results obtained by using the IR images.

of the wavelength range 550–625 nm by 0.6 and that of 625–700 nm by 2.8. Then, from the changed spectral reflectance, we calculated the visible light components. From the obtained results, it can be seen that the autumn color is assigned to only the detected green plants. Therefore, although these results are simple examples, they indicate that the use of spectral reflectance provides breakthroughs for several color processing applications such as color transfer.

V. CONCLUSIONS

In this paper, we proposed an NMF-based spectral reflectance estimation method using a Visible-and-NIR image and an NIR image. The proposed method enables approximation of spectral reflectance in the lower-dimensional subspace spanned by non-negative bases obtained from a training spectral reflectance dataset based on NMF. The spectral reflectance can be successfully estimated in this low-dimensional space instead of estimating it directly since the estimation target can be effectively reduced. Furthermore, the proposed method also approximates the spectrum power distribution of the light source by the combination of the direct light component and the scattered light component. Therefore, the problem of directly estimating the spectrum power distribution can be reformulated as a problem of only estimating the combination parameter. Not only spectral reflectance estimation but also the spectrum power distribution of the light source can be solved by simpler problems.

As shown in the experimental results, the proposed method enables successful estimation of spectral reflectance. Furthermore, the results obtained by applying the proposed method to two tasks, extraction of visible light components and detection of green plants, show the effectiveness of our method for real life applications. Since spectral reflectance has much more
information than do RGB values, it provides breakthroughs to several fundamental applications.

In this paper, we assume that the Visible-and-NIR image and the NIR image are taken in the daytime for using a fixed direct light component and scattered light component. If the imaging environment changes, the optimal values of these two components also change. Therefore, an estimation method of the imaging environment is necessary for improving the performance of the proposed method. This topic will be addressed in a future work.

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References


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