LIGHT TRANSPORT COMPONENT DECOMPOSITION USING MULTI-FREQUENCY ILLUMINATION

Art Subpa-asa⋆† *Yinqiang Zheng*† *Nobutaka Ono*† *Imari Sato*⋆†

⋆ Tokyo Institute of Technology
† National Institute of Informatics

ABSTRACT

Scene appearance is a mixture of light transport phenomena ranging from direct reflection to complicated effect such as inter-reflection and subsurface scattering. To decompose scene appearance into meaningful photometric components is very helpful in scene understanding and image editing. However, it has proven to be a difficult task. In this paper, we explore the difference of direct components obtained by multi-frequency illumination for light transport component decomposition. We apply independent vector analysis (IVA) to this task with no fixed constraints. Experiment results have verified the effectiveness of our method and its applicability to generic scenes.

***Index Terms*—** Light transport separation, Direct reflection, Subsurface scattering, Inter-reflection

1. INTRODUCTION

Because of the complex interaction between illumination and objects, the appearance of a scene is composed of various light transport phenomena, ranging from simple direct reflection to complicated effect such as subsurface scattering, volumetric scattering and inter-reflection, as illustrated in Figure 1. Ability to distinguish between these meaningful photometric components is essential to understand properties of an object in observation. Unfortunately, separation of such components in computer has proven to be a challenging task.

Light transport can be separated into direct component and global component, accounting for direct reflection and other global transport phenomena by using high frequency spatial illumination generated by an ordinary projector [1]. However, to further separate the global component apart is difficult in the presence of single frequency illumination patterns. Multiple frequency illumination has been used to decompose the scene into multiple meaningful photometric components, on the basis of the fact that the extracted direct component and global component depend on the frequency of projected illumination patterns. This dependence has shown to be stable and significant enough to separate multiple layers of a translucent object using multiple frequency illumination [2].

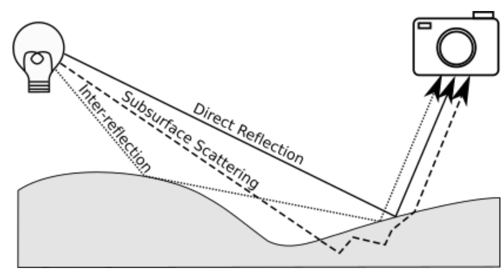

Fig. 1. Illustration of light transport in real environment. Perceived light in the same location is combinations of direct reflection, sub-surface scattering, inter-reflection and other photometric effects.

In this paper, we are aiming at a multiple frequency separation method for general scenes with fewer restrictions. We use multiple frequency direct components for separation, which are shown to be a linear combination of light transport components and abundance coefficients. Independent vector analysis (IVA) [3, 4] is used to solve the resulting blind source separation problem, without ambiguity in permutation between color channels. Similar to [1], our setup only requires a simple off-the-shelf camera and projector system.

2. RELATED WORKS

Nayar et al. [1] proposed a fast separation method that decomposed the scene into two components: direct and global components. The direct component accounts for direct reflection bouncing off object's surface, while the global component includes other light transport phenomena such as subsurface-scattering and inter-reflection. This method is composed of an off-the-shelf camera-projector system. A serial of spatially shifting high frequency illumination patterns, like checker and sinusoid pattern, are used to differentiate each pixel when lit and unlit by the light source. This method has been applied for various task such as 3D reconstruction [5, 6] , analyzing scattering conditions [7, 8] and camera calibration [9]. Extended researches, such as motion compensation [10], multiplexing pattern [11] and multiple projections [12, 13], have been conducted to improve separation quality and elim-

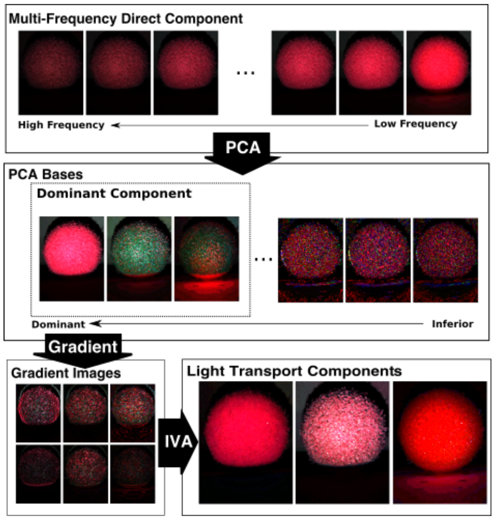

Fig. 2. Overview of our proposed method. Multiple frequency direct components obtained from different illumination patterns are compressed by using PCA. The dominant components are separated into different light transport components by applying IVA on gradient images.

inate various imaging limitations. However, these methods are unable to separate additional components beyond direct and global. On the other hand, some researches focus on separating specific domains. Specific bounces of inter-reflection are separated by using duality between forward and inverse light transport [14]. Specular components are separated by using cues in chromaticity [15].

Direct components from different illumination frequency have been used to separate additional components. Separation of direct component, near range global component and far range global components has been addressed by using binary [16] and sinusoid patterns [17]. Layers of multiple translucent objects have been separated by using depth dependent scattering model [2]. However, these methods use restricted models, which only work well for designated task.

Moreover, special hardware modules have been introduced for light transport component separation task. For example, a super high speed camera [18], which can differentiate each component from response time, has been used to capture time-of-flight image; Digital micro mirror devices, placed in front of sensor to create dual codes between camera and projector, has been used to separate direct, near range and far range global component from a single shot measurement [19]. In this paper, we tackle a difficult problem of decomposing scene appearance into meaningful photometric components by examining direct components obtained by multi-frequency illumination.

3. PROPOSED DECOMPOSITION METHOD

3.1. Direct and Global Components

Under uniform light, the intensity i of the p-th pixel consists of two components: direct component i_d and global component i_g, which can be described as

$$i(p) = i_d(p) + i_g(p). \tag{1}$$

While direct component represents a direct reflection of light source illumination on object surface, the source of global component is ambiguous and difficult to interpret. In reality, global component contains effect of indirect illumination from the scene, such as subsurface scattering, volumetric scattering, inter-reflection, which can be defined as follows

$$i_g(p) = i_{g1}(p) + i_{g2}(p) + ... + i_{gn}(p), \tag{2}$$

in which n denotes the number of individual global components.

Then, Equation 1 and 2 can be combined into

$$i(p) = i_d(p) + i_{g1}(p) + i_{g2}(p) + ... + i_{gn}(p). \tag{3}$$

In practice, direct and global components separated by using high frequency pattern L with spatial frequency f are an approximation to real direct and global components, whose accuracy depends on frequency of projected pattern. We assume that separated direct and global components are linear combination of ideal individual component as follows

$$\hat{i}_d(p, f) = \alpha_d(f)i_d(p) + \alpha_{g1}(f)i_{g1}(p) + ... + \alpha_{gn}(f)i_{gn}(p), \tag{4}$$
$$\hat{i}_g(p, f) = \beta_d(f)i_d(p) + \beta_{g1}(f)i_{g1}(p) + ... + \beta_{gn}(f)i_{gn}(p). \tag{5}$$

Since the summation of direct and global components should be the same as scene appearance under uniform light, such that $i(p) = \hat{i}_d(p, f) + \hat{i}_g(p, f)$ and $\alpha + \beta = 1$, we can eliminate coefficient β in global component as in the following equation:

$$\hat{i}_g(p, f) = (1 - \alpha_d(f))i_d(p) + (1 - \alpha_{g1}(f))i_{g1}(p) + ... + (1 - \alpha_{gn}(f))i_{gn}(p). \tag{6}$$

Noted that, by using direct and global components from single frequency illumination, it is infeasible to obtain more light transport components, because the number of observations is smaller than that of unknown components.

3.2. Multiple Frequency Linear Unmixing Model

To capture enough information for each component, we first obtain a serial of direct and global components by using the fast separation method [1] with varying frequency in the illumination patterns. According to Equation 6, direct and global components at each frequency contain the same information, we therefore use the direct components for further separation, which are called as *multiple frequency direct components*. The linear model in Equation 4 can be written into matrix form

$$D = AX, \tag{7}$$

$$D = \begin{bmatrix} \hat{\mathbf{d}}(f_1) \\ \hat{\mathbf{d}}(f_2) \\ \vdots \\ \hat{\mathbf{d}}(f_m) \end{bmatrix}, A = \begin{bmatrix} \alpha_d(f_1) & \dots & \alpha_d(f_m) \\ \alpha_{g1}(f_1) & \dots & \alpha_{g1}(f_m) \\ \vdots & \ddots & \vdots \\ \alpha_{gn}(f_1) & \dots & \alpha_{gn}(f_m) \end{bmatrix}^T, X = \begin{bmatrix} \mathbf{d} \\ \mathbf{g_1} \\ \vdots \\ \mathbf{g_n} \end{bmatrix},$$

in which $\hat{\mathbf{d}}(f_m)$ is a row vector of extracted direct component at frequency m, $\mathbf{d}$ is a row vector of real direct reflection and $\mathbf{g_n}$ is a row vector of n^{-th} real global component.

3.3. PCA Dimensionality Reduction

In practice, it is difficult to exactly determine the number of component n in the scene. If the preset number n is more than needed, many components will be contaminated by noise arising from the camera-projector system. Moreover, coefficient of less significant component is much lower in comparison to other components which affected validity of our linear model. To avoid this issue, we resort to dimensionality reduction to pick up the dominant components, rather than separating light components on the basis of the multiple frequency direct components. Here, we use principal component analysis (PCA) to extract the principle components of D. By examining the eigenvalues, we retain the most dominant three components of D as $\hat{D}$. As a result, the separation task in Equation 7 can be adapted into

$$\hat{D} = \hat{A}\hat{X}. \tag{8}$$

3.4. IVA Separation

To estimate independent components in matrices $\hat{X}$ from the known matrix $\hat{D}$, we apply a blind source separation technique, such as Independent Component Analysis (ICA). However, since structures of images are represented in three color channels, the separation technique has to be applied to each different channel separately, which leads to a permutation problem between channels.

To avoid such ambiguity, we use Independent Vector Analysis (IVA), which is designed to perform blind source separation while preserving relation between different channels of observed data [20]. It will estimate an unmixing matrix $W = \hat{A}^{-1}$. However, it is usually assumed in IVA that the data should comply with symmetric zero-mean distribution. Therefore, rather than using IVA on $\hat{X}$ directly, we calculate the gradient images of $\hat{X}$ and use them to estimate W.

After W is estimated from gradient images, reconstruction of light component $\hat{X}$ can be achieved by using

$$\hat{X} = \hat{A}^{-1}\hat{D} = W\hat{D}. \tag{9}$$

The chart of our separation method is shown in Figure 2.

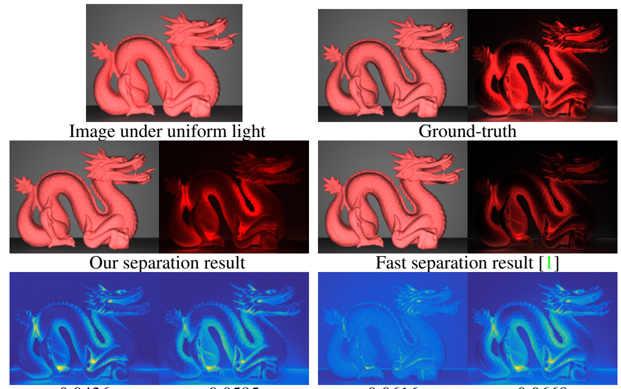

Fig. 3. Experiment results on simulated images. The image under uniform light and the ground-truth separation are shown in the 1st row. Separation results of our method and the competing method [1] are shown in the 2nd row, and the error images are in the 3rd row.

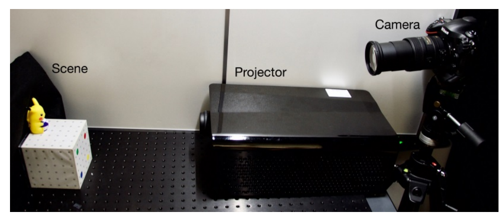

Fig. 4. Our capturing system consists of an off-the-shelf RGB camera and projector.

4. EXPERIMENTAL RESULTS

We implemented our separation method on Matlab 2014a. The multi-frequency direct components were calculated by using the fast separation method from a scene projected by series of horizontal and vertical shifted checker patterns with varied pattern resolution. We used the state-of-the-art IVA algorithm AuxIVA [20] for separation, and the number of iterations is 10. We conducted experiments on both simulated images and real images captured by a camera-projector system.

To examine whether our separation results were close to the ground-truth light transport components, we used a physics based rendering tool [21] to render scenes for our simulation experiment. For simplicity, light transport components were limited to direct reflection and inter-reflection only. The ground-truth direct reflection was simulated by limiting the maximum number of light bounce to be one. The ground-truth inter-reflection was calculated by subtracting the rendered scene in uniform light by the direct reflection. We also rendered scenes under checker pattern illumination with varying frequency. Then, we evaluated our results by comparing the absolute error between the ground-truth and

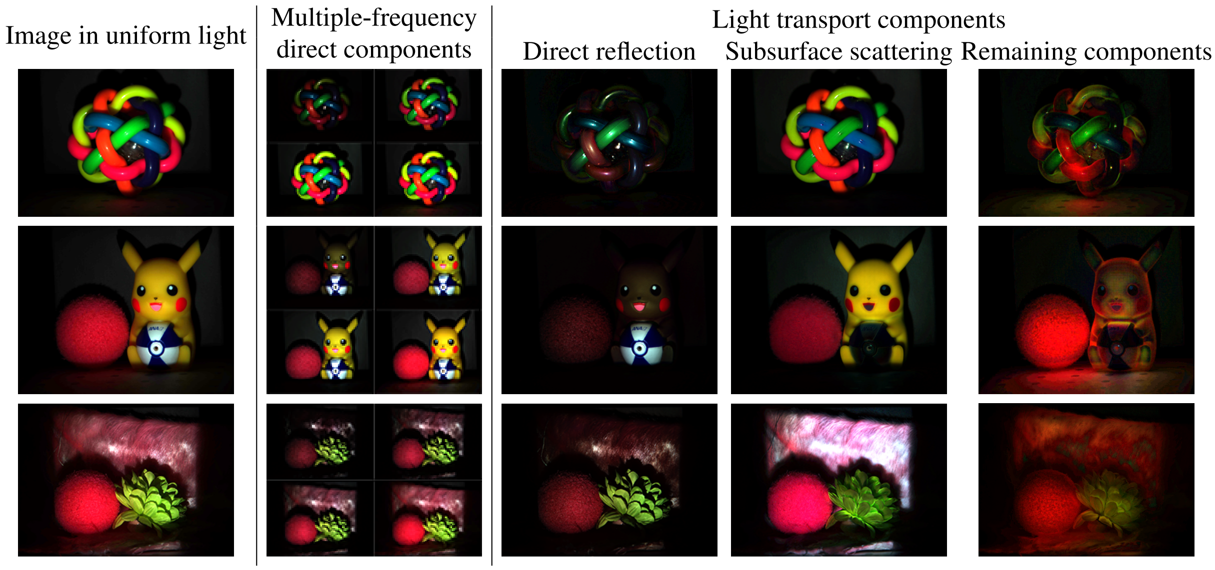

Fig. 5. Separation results on real images. The left most column shows images under uniform light, the middle column shows input multi-frequency direct components, and the right column shows separated components after intensity normalization for better visualization.

the separated component. As noted in [2], the direct and global components of a scene extracted by the fast separation method [1] vary depending on the frequency of projected illumination patterns. It is thus essential to set a proper frequency to illumination n^{th} to obtain meaningful components such as direct reflection and inter-reflection. As shown in Figure 3, our method automatically finds meaningful structures of the scene with less decomposition errors.

To capture real images, we built a simple camera-projector system. We aligned a Light Commander Projector and a Nikon D4S camera into roughly identical perspective to reduce geometric distortion. Our system is shown in Figure 4. We projected checker patterns with the varying size of pattern pitch from 8 to 96 pixels, which step up at every 4 pixels, and captured 36 images at each frequency. In this experiment, we selected top three components to represent light transport components.

Samples of our experimental results are shown in Figure 5. For better visualization, we have rescaled the intensity range of each separated component. From Figure 5, we can see that our method clearly separates the scene into three meaningful components. For example, the direct component of the colorful plastic toy (1st row) includes direct diffuse reflection and specular reflection. The second component shows the scattering of color inside the toy. The last component mainly includes inter-reflection within the toy itself and inter-reflection between the toy and the floor, which exhibit color saturation in comparison to real color of the object. The 2nd row shows the separation results of a red ball and a plastic doll (Pikachu), from which the direct surface reflection, subsurface scattering and inter-reflection can be clearly seen in each individual component. The same observation applies to the results of the scene in the 3rd row, which is composed of a red ball, a green flower and a piece of cloth. We clearly see that each component has been separated nicely regardless of color and shape differences between objects. These results verify the effectiveness of our method and its applicability to generally complex scenes.

5. CONCLUSION AND DISCUSSION

In this paper, we have proposed a light transport component separation method from multiple frequency direct components by using Independent Vector Analysis. Our method requires only a off-the-shelf camera-projector setup, which can be easily prepared. Moreover, it is flexible to handle multiple components without restrictive models. Quantitative and qualitative results have demonstrated the effectiveness of our method.

As for future study, we aim to improve separation quality of our method further. Illumination patterns with continuous gradient instead of binary patterns should be introduced to increase stability of multi-frequency direct components, so as to handle scene objects with very sharp edges. Another potential improvement is to avoid negative-valued pixels included in separated light transport components, by incorporating non-negative constraints into separation.

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