Acceleration of the reflectance field acquisition using independent component analysis

M.L. Rosas-Cholula, and M.O. Arias-Estrada
Department of Computer Sciences
National Institute of Astrophysics, Optics and Electronics, INAOE
Puebla, México
{mluisa,ariasmo}@inaoep.mx

Abstract—**In order to generate photorealistic images, a central problem in computer graphics is the description of an object reflectance model. The reflectance field technique describes the object surface properties and can be used for photorealistic rendering. The reflection of surfaces can be described as a high dimensional reflectance function. For complex surfaces, an analytical model is not always easy to formulate, therefore the direct real-world surface acquisition is preferred. The reflectance is typically acquired with a camera or array of cameras that capture the reflectance field of the object surface but the reflectance information can be composed of thousands of images, depending on the surface material properties and the camera resolution. In this work we proposes a systematic strategy that incorporates Independent Component Analysis (ICA) to acquire the reflectance field and reducing by orders of magnitude the required number of captured images and keeping the same reflectance field quality. In our experiments, a reflectance field can be obtained with only 26 images, compared to the classical approach that require thousands of images, with an error less than 0.19%.**

Keywords-component; reflectance field; independent component analysis; computer graphics

I. INTRODUCTION

To obtain the reflectance field for describing the surface properties of an object in a scene is one of the central problems in computer graphics. However, the formulation of analytical models for complex surfaces is not always an easy task. An alternative approach is to capture the reflectance information from real-world surfaces. This acquisition is carried out, for capturing with a camera or array of cameras a set of data that describes the transfer of energy between a light field of incoming rays (the illumination) and a light field of outgoing rays (the view). Such set of data is known as the Reflectance Field [1]. For obtaining the reflectance field of a scene, thousands of images are acquired depending on the optical properties of the object placed in the scene and how much variation is permitted in the illumination and viewer position [2,3,4].

The traditional technique to acquire the reflectance field of an object consists in illuminating and capturing pixel by pixel the object placed in the scene using a video projector. In order to accelerate the acquisition, some algorithms are devoted to parallelize the capture. To illuminate multiple pixels at the same time, it is possible only with the assumption that each projected pixel affects a small and localized region of the scene. Even so, the amount of images that composes the reflectance field is extremely large (thousands of images) [5].

This paper proposes a systematic strategy that uses independent component analysis (ICA) to acquire the reflectance field. Our method takes advantage of the fact that the pixels parallel illuminated affect local regions of the scene. We consider the transfer of energy between the incoming and outgoing light fields as signal mixtures in order to use an ICA approach to decompose the signal mixtures into statistically independent signals. Our procedure avoids the need of analytical model of the reflectance field, it reduces the images required to describe the field and our strategy keeps the same reflectance field quality as the traditional approach.

II. REFLECTANCE FIELD AND INDEPENDENT COMPONENT ANALYSIS

The light fields are used to describe the radiance at each point x and in each direction ω in a scene. Ignoring wavelength and fixing time, this is a 5D function which we denote by $\widetilde{L}(x,\omega)$. Thus, $\widetilde{L}(x,\omega)$ represents the radiance leaving a point x in direction ω.

Levoy and Hanrahan [2] observed that if the viewer is moving within the unoccluded space, then the 5D representation of the light field can be reduced to 4D. We can characterize this function as $L(\psi)$, where ψ specifies a point and an incoming direction on a sphere [1]. A 4D light field can be used to generate an image from any viewing position and direction, but it will always show the scene under the same lighting. In general, each field of incident illumination on a scene will induce a different field of exiting illumination from the scene. Debevec et al [1] showed that the exiting light field from the scene under every possible incident field of illumination can be represented as an 8D function called the reflectance field: $R(L_i(\psi_i); L_0(\psi_0)) = R(\psi_i; \psi_0)$

Here, $L_i(\psi_i)$ represents the incident light field on the scene, and $L_0(\psi_0)$ represents the exiting light field reflected off the scene. In order to work with discrete forms of these functions, the domain ψ of all incoming directions can be parameterized by an array indexed by i. The outgoing direction corresponding to an incoming direction is also parameterized by the same index, i. Now, consider emitting unit radiance along ray i towards the scene (e.g., using a projector). The resulting light field, which is denoted by vector $\mathbf{t}_i$, captures the full transport of light in response to this impulse illumination. This is called the impulse response [6] or the impulse scatter function [7]. We can concatenate all the impulse responses into a matrix $\mathbf{T}$ which we call the light transport matrix:

$$\mathbf{T} = [\mathbf{t}_1 \mathbf{t}_2 \ldots \mathbf{t}_n] \tag{1}$$

Since light transport is linear, any outgoing light field represented by a vector $\mathbf{L}_0$ can be described as linear combination of the impulse responses, $\mathbf{t}_i$. Thus, for an incoming illumination described by vector $\mathbf{L}_i$, the outgoing light field can be expressed as:

$$\mathbf{L}_0 = \mathbf{T}\mathbf{L}_i \tag{2}$$

The light transport matrix $\mathbf{T}$, is thus the discrete analog of the reflectance field $R(L_i(\psi_i); L_0(\psi_0))$.

In the other hand, the independent component analysis is a method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the source signals [8]. Assume that we observe n linear mixtures $x_1, \ldots, x_n$of n independent components

$$x_i = a_{i_1}s_1 + a_{i_2}s_2 + \cdots + a_{i_n}s_n, \text{ for all } i \tag{3}$$

In the ICA model, it is assumed that each mixture x_i as well as each independent component s_k is a random variable. The observed values x_i are a sample of this random variable.

It is convenient to use vector-matrix notation instead of the sums like in the previous equation. Let us denote by $\mathbf{x}$ the random vector whose elements are the mixtures $x_1, ..., x_n$ and likewise by $\mathbf{s}$ the random vector with elements $s_1, ..., s_n$. Let us denote by $\mathbf{A}$ the matrix with elements a_{ij}. Using the vector-matrix notation, the above mixing model is written as

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{4}$$

The statistical model in 4 is called independent component analysis, or ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_i. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. All we observe is the random vector $\mathbf{x}$, and both $\mathbf{A}$ and $\mathbf{s}$ have to be estimated by using such vector.

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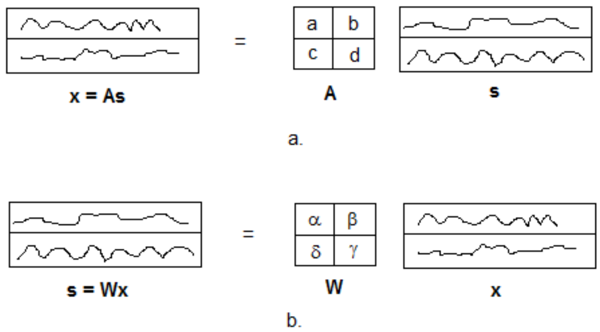

Figure 1. Schematic diagram of vector-matrix representation of mixing (a) and unmixing (b). (a): Two source signals are transformed by an unknown matrix A to form two signals mixtures. (b): Two signals mixtures are transformed by a unmixing matrix W to form two estimated source signals.

The starting point for ICA is the assumption that the components s_i are statistically independent. Then, after estimating the matrix $\mathbf{A}$, we can compute its inverse $\mathbf{W}$, and obtain the independent component simply by

$$\mathrm{s} = \mathrm{W}\mathrm{x} \tag{5}$$

ICA is very closely related to the method called: blind source separation (BSS) or blind signal separation. A "source" means here an original signal. "Blind" means that the mixing matrix is unknown. The Fig. 1 shows the mixing (top) and unmixing (bottom) process.

III. Independent Component Analysis Of The Reflectance Field

Consider the scene configuration in Fig. 2. All the scene is illuminated parallel by a light source $\mathbf{L}_i$.

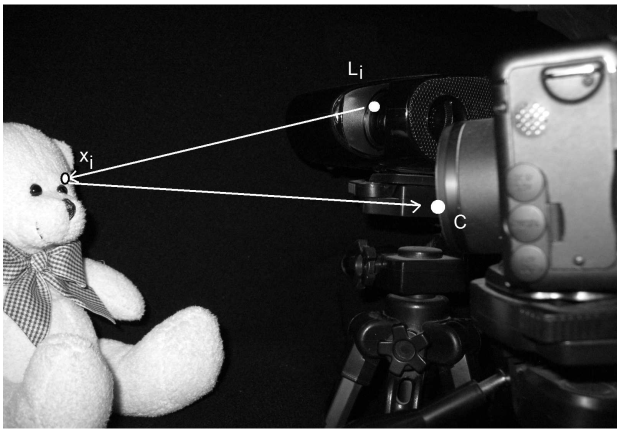

Figure 2. The scene is illuminated parallel by a light source $\mathbf{L}_i$. A particular point in the scene x_i will reflect light to the camera C. The outgoing light field $\mathbf{L}_0$ is the reflected intensity in the direction of C from the point x_i.

A particular point in the scene x_i will reflect light to the camera C according to 2, the outgoing light field represented by the vector $\mathbf{L}_0$ is the reflected intensity in the direction of C from the point x_i and it can be considered as a signal mixture of the impulse responses, $\mathbf{T}$.

According to the ICA model, these independent components t_i cannot be directly observed. $\mathbf{L}_i$ is the incident light intensity at point x_i.

Considering 3, the observed values from the point x_i are samples of $\mathbf{L}_0$ and can be expressed as

$$\begin{array}{c} L_0(x_1) = (L_0(x_1^1), L(x_1^2), \ldots, L_0(x_1^N)) \\ L_0(x_2) = (L_0(x_2^1), L_0(x_2^2), \ldots, L_0(x_2^N)) \\ \vdots \\ L_0(x_i) = (L_0(x_i^1), L_0(x_i^2), \ldots, L_0(x_i^N)) \end{array} \tag{6}$$

where the superscripts specify the identity of the intensity level of the $\mathbf{L}_0$ sample and the subscripts specify the identity of the reflectance field element.

Following the ICA model (see 5), we can calculate $\mathbf{T_e}$ as an estimated of $\mathbf{T}$ (light transport matrix), such as

$$\mathbf{T_e} = \mathbf{W}\mathbf{L_0} \tag{7}$$

IV. Test Capture and Results

The capture setup for the experiments requires a projector and a camera. There is no restriction on the location of the camera and the projector. Also there is no geometric calibration required. Capturing the reflectance field refers to project patterns towards a scene. The pattern is projected by lighting every single pixel of the light source (projector). Every point of light reflected from the scene is imaged by a sensor (camera). The set of images captured will compose the reflectance field.

Figure 3. Camera-projector assembly. The object in the scene is fixed and it is located in the field of view of the camera and projector. In the experiments, we are using a Samsung digital projector with a resolution of 640x480 pixels, and a Canon PowerShot-G5 camera with a resolution of 640x480 in B/W.

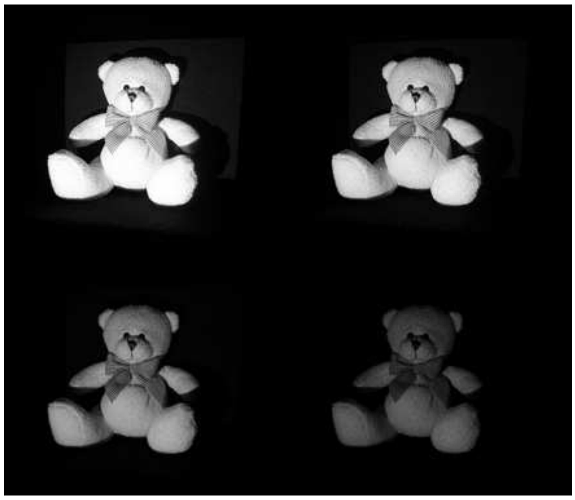

Figure 4. Example of a scene illuminated with 4 different levels of gray.

In the experiments, the reflectance field by illuminating pixel by pixel (brute-force scan) onto the scene is acquired as in [5]. After that, we obtain the reflectance field by our method. To define the reflectance field quality acquired with our method, we compare the images synthesized from both reflectance fields and a RMS error is computed.

The system setup is composed by a Samsung digital projector with a resolution of 640x480 pixels, and a Canon PowerShot-G5 camera with a resolution of 640x480 in B/W (Fig. 3). The object in the scene is fixed and it is located in the field of view of the camera and projector.

The brute-force-scan method requires that the projector of the system setup with resolution $p \times q$ shine light onto a scene. Every point of light reflected from the scene is imaged by the camera of resolution $m \times n$. The number of images captured by the camera is: $p \times q$ images. The images are stored in a transport matrix T (see 1) of size $mn \times pq$. The matrix size depends on the kind of object to be recovered.

In our method all the scene is parallel illuminated by the projector it is, every pixel of the projector or points of light with resolution 640x480 represented by $\mathbf{L}_i$ are lighted up. The scene will reflect light to the camera with resolution of 640x480 that is, 640x480 signal mixtures of the impulse responses, $\mathbf{T}$ are received. We do amplitude variations by projecting N different levels of gray of sequential patterns. The Fig. 4 shows an example of a scene illuminated with 4 different levels of gray.

The experiments were carried out with $N = 26$ that is, 26 images with amplitude variations of 10 levels of gray were captured. The value of N was defined by minimizing the RMS error from the comparison of the reflectance field acquired pixel by pixel and the reflectance field obtained with our method by doing amplitude variations of levels of gray (1 to 255 amplitude variations it is, 1 to 255 images).

According to the 7, every vector $\mathbf{L}_0(x_i)$ is composed by the N amplitude variations and $0 \leq i \leq$640x480. This means that we can obtain the 4D reflectance field with N images. The Fig. 5 shows the image synthesized by illuminating pixel by pixel the scene (top) and the image synthesized by using our method (bottom). The Fig. 6 shows the RMS error calculated by doing a comparison between the image synthesized by illuminating pixel by pixel and the image synthesized by using our method.

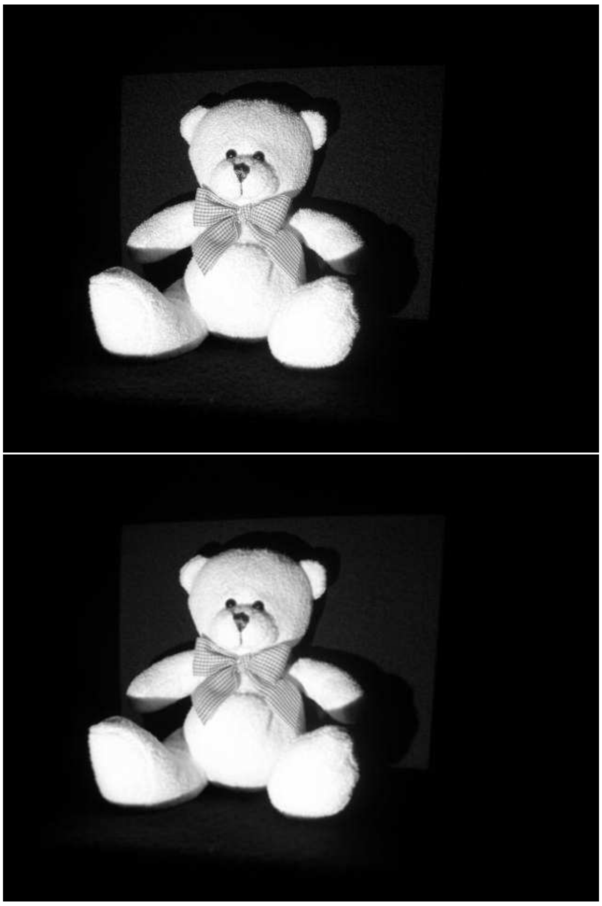

Figure 5. Images synthesized by illuminating pixel by pixel the scene (top) and by our method (bottom).

V. DISCUSSION

When the projection and capturing are performed by using the brute-force scan and the setup described in the experimental results section, 640x480 images were captured. In our method, only 26 images were acquired that is, with our method we were able to decrease the amount of images for the reflectance field composition up to 99%. The RMS of the example shows that the reflectance field quality is maintained. The Fig. 7 summarizes the results of our method.

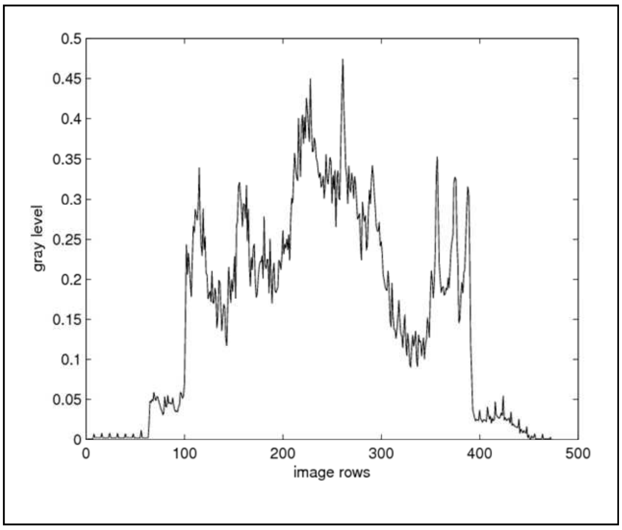

Figure 6. RMS of the example, it is calculated by doing a comparison between the image synthesized by illuminating pixel by pixel and the image synthesized by using our method.

Scene	Brute-Force Scan Size (TB)	Brute-Force Scan Time (Days)	Brute-Force Scan Images (#)	Our method Size (MB)	Our method Time (Min)	Our method Images (#)	Our method RMS BFS vs Our method (levels of gray)
Example	0.6	107	307200	78	13	26	0.4

Figure 7. Relevant data (size, time, number of images and RMS) for the example scene captured using our method.

VI. CONCLUSIONS

We have implemented a system setup composed by a camera and a projector to obtain the reflectance field of objects with an anisotropic BRDF (4D) from their surface. We proposed a method for accelerating the acquisition of the reflectance information using independent component analysis approach. We proposed a method that considers the outgoing rays of the light field as statistically independent signals. These independent signals are obtained from the decomposition of a set of signal mixtures. These signal mixtures are acquired by taking images of the scene when it is illuminated by a projector with all its pixels turned on and when the illumination suffers amplitude variations. The theory and experiment have demonstrated the ability to decrease the number of images for the reflectance field composition up to 99%.

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