Dense Light Transport for Relighting Computation Using Orthogonal Illumination Based on Walsh-Hadamard Matrix

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SUMMARY We propose a practical method that acquires dense light transports from unknown 3D objects by employing orthogonal illumination based on a Walsh-Hadamard matrix for relighting computation. We assume the presence of color crosstalk, which represents color mixing between projector pixels and camera pixels, and then describe the light transport matrix by using sets of the orthogonal illumination and the corresponding camera response. Our method handles not only direct reflection light but also global light radiated from the entire environment. Tests of the proposed method using real images show that orthogonal illumination is an effective way of acquiring accurate light transports from various 3D objects. We demonstrate a relighting test based on acquired light transports and confirm that our method outputs excellent relighting images that compare favorably with the actual images observed by the system.

key words: light transport, relighting, color crosstalk, Walsh-Hadamard matrix, orthogonal illumination

1. Introduction

The projector is a flexible illumination device that offers arbitrary scaling, and provides augmented reality, computer-human interaction, and projection-based display in real space [1]–[5]. In particular, projection mapping is the most popular projection-based display technology in amusement parks, entertainment events, and huge 3D advertisements [6]. Conventional approaches demand the design of a model to simulate image displays according to the actual 3D structures, as well as time-consuming adjustments of the system parameters and CG contents to suit the models. It is found that precomputation-based rendering [7]–[9], so-called relighting [10]–[14], creates virtual image displays on 3D structures with varying illumination. Considering that relighting simulations can demonstrate projection mapping in advance, a system that has no complicated 3D design requirements or calibration setup is needed to better support CG creators and system operators.

If we use an uncalibrated projector-camera system to relight unknown 3D objects, we rely on light transports, i.e., the geometric and photometric correspondences between all projector pixels and all camera pixels [8], [15]. Light transports describe various reflection lights via the 3D structure. For instance, by introducing brute-force scanning (BFS), which sequentially illuminates each pixel on the projector plane, we can simply find the camera pixels that connect via the light transports to each projector pixel. We often use a light transport matrix in which each column represents the camera response image that corresponds to each projector light [15]. Given a projector vector as arbitrary illumination, the matrix-vector product created from the light transport matrix and the vector yields the relighting image under the illumination. By focusing on the rank of light transport matrix, the existing methods that acquire light transports are roughly classified into the following. On the assumption that the light transport matrix is both sparse and high-rank, the acquisition methods used in [8], [15], [16] handle projector illumination patterns with both high and low frequencies. As a new trend, compressed sensing techniques are applied to reconstruct the light transport matrix [17], [18]; the matrix estimated by the compressive light transport essentially holds the property of sparsity. In contrast, low-rank matrix approximations assume that high frequency projector lights are seldom present in the camera responses and acquire dense light transports from 3D target by using a system with custom optical apparatus [19]–[21].

For relighting with excellent presence that replicates real environments, we need to consider not only direct reflection light but also the global reflection light radiated from the entire environment because it yields key visual effects in real world scenes [8], [22], [23]. The former is caused by direct illumination from a point source, and the latter is caused by indirect illumination due to other points in a scene, e.g., inter-reflection, subsurface scattering, and translucency. As noted in [24], single light source does not have sufficient intensity to produce images with a high signal-to-noise ratio. Since BFS basically uses a point light source to obtain light transports, the camera detects impulse responses on the image plane. Even if we try to adjust the optical parameters via camera settings, e.g., shutter speed or aperture, within the limited dynamic range of the camera’s response sensitivity, off-the-shelf cameras may not accurately detect the global light which corresponds to each isolated illumination against image noise. The previous methods that obtain sparse light transports also hold the property of high-rank matrix, hence they cannot simultaneously acquire direct light transport and global light transport in principle. In contrast, the method published in [16], which uses both a gray code pattern and a multiplexed illumination pattern [25], aims to acquire global light transport as well as direct light transport. The approach basically manipu-
lates the multiplexed illumination pattern on projector pixel blocks divided in a grid shape to acquire global light transport. Since the light transports acquired by the pixel blocks generate undesirable artifacts at block boundaries, it fails to achieve high-quality relighting by using direct and global light transports. The global reflection light is traceable to the complicated illumination radiated from the entire environment, so a desirable system feature is employing a majority of projector pixels as the light source and acquiring dense light transports related to global reflection light. The above-mentioned methods of acquiring dense light transports will yield global reflection lights in real environments. However, since they drastically reduce the rank of the light transport matrix, it seems that relighting simulations based on these light transport matrices are restricted to simple illumination variations [21]. Due to their low-rank property, it is not evident that they can support the use of real photographs or artistic illuminations in projection mapping.

As mentioned above, the column vectors of the light transport matrix originally represent the camera responses yielded by the system given the projector illumination patterns. Depending on the illumination to be used for relighting, however, not all camera responses contribute to relighting computation, i.e., the product of the light transport matrix and the illumination vector. In order to grasp the effective rank of the light transport matrix for relighting computation, we focus on the fact that the orthonormal basis allows an arbitrary illumination to be expressed uniquely. If the projector illumination patterns for acquiring light transports are designed based on the orthonormal basis, decomposing the given illumination vector by using the illumination patterns enables us to find the effective illumination components that contribute to relighting computation. Following a component analysis, our approach collects only those light transports that virtually supports relighting computation, and uses them to form a compressed light transport matrix. This means that the rank of the compressed light transport matrix depends on the number of effective illumination components. Based on this idea, we propose a practical method that simultaneously acquires the direct and global light transports to obtain a dense and high-rank light transport matrix; it supports a wide variety of relighting through the use of photographic, artistic, and complex illuminations. Acquisition of a light transport matrix involves designing a set of projector illuminations and storing the corresponding camera responses in a sequence [26]. We employ the projector illumination patterns (orthogonal illumination) generated by a Walsh-Hadamard matrix, in which one half of the elements are used for positive pattern and the other half are used for negative pattern. In digital signal processing, Hadamard codes offer practical error detection and correction when transmitting messages over very noisy or unreliable channels. A lighting scheme controlled by a Hadamard code is also applied for multiplexing in image-based rendering [24]. Note here that we assume that projectors and cameras inherently focus on spectrum components in the visible light region. Although most previous methods acquire light transports by using white illumination [15], [16], [19], [20], we obtain dense light transports by handling color orthogonal illumination on the assumption of color crosstalk between the projector’s and camera’s channels in the system [27]–[29]. In addition, we utilize the acquired light transports for relighting computation, where we do not employ straightforward matrix-vector product of the light transport matrix and an illumination vector. Given the illumination vector, we analyze the illumination components that are obtained uniquely by the orthogonal illumination, and then use a compressed light transport matrix constructed from the effective illumination components to efficiently carry out relighting computations.

This paper is organized as follows: Sect. 2 describes how to determine the light transport matrix by using sets of color orthogonal illuminations and the corresponding camera responses. Section 3 proves that we design color orthogonal illuminations based on a Walsh-Hadamard matrix and acquire dense light transports with color crosstalk. We then introduce a relighting computation that uses effective light transports represented by orthogonal basis. Section 4 demonstrates that orthogonal illumination is an effective way of acquiring accurate light transports from various 3D objects. Our experiments on a relighting test confirm that our method achieves excellent relighting images, which compare favorably with the actual images observed by the system. Finally, Sect. 5 concludes this study and mentions future work.

2. Light Transport Matrix with Color Crosstalk

We assume that the camera plane has $M \times M$ pixels and the projector plane has $N \times N$ pixels for convenience. We denote the $r$, $g$, and $b$- channel’s projector illuminations by the $N^2$- dimensional vectors $\mathbf{P}_r$, $\mathbf{P}_g$, and $\mathbf{P}_b$, respectively. By considering the color crosstalk between the projector’s and camera’s channels in the system, we represent the camera responses of $r$, $g$, and $b$-channels connected with the $\beta$- channel, $\beta \in \{r, g, b\}$, of the projector illumination by the $M^2$- dimensional vectors $\mathbf{C}_{\alpha \beta}$, $\mathbf{C}_{\beta \alpha}$, and $\mathbf{C}_{\beta \beta}$. We describe the geometric and photometric correspondence with crosstalk between all projector pixels and all camera pixels by,

$$
\mathbf{C}_{\alpha \beta} = \mathbf{T}_{\alpha \beta} \mathbf{P}_\beta + \mathbf{F}_\alpha, \quad \alpha, \beta \in \{r, g, b\},
$$

where matrix $\mathbf{T}_{\alpha \beta}$ represents the $M^2 \times N^2$ light transport matrix that transports projector pixels of $\beta$-channel to camera pixels of $\alpha$-channel. Vector $\mathbf{F}_\alpha$ represents $\alpha$-component of ambient light, which includes black offsets from the projector, as detected by the camera response. If the color crosstalk in the projector-camera system can be substantially ignored, we set $\mathbf{T}_{\alpha \beta} = \mathbf{0}$, $\alpha \neq \beta$, in Eq. (1).

We acquire various light transports via an unknown 3D structure by handling $K$-kinds of projector illuminations. In Fig. 1, the system outputs a projector illumination and obtains a camera response, one after the other. We denote the $k$-th projector illumination ($\beta$-channel) by the $N^2$- dimensional vector $\mathbf{F}_k^{(\beta)}$, and the $k$-th camera response ($\alpha$-
channel) connected with the $\beta$-channel of the $k$-th projector illumination by the $M^2$-dimensional vector $C_{\alpha|\beta}$. When projector illumination vectors $\{P_{\beta}^{(1)}, P_{\beta}^{(2)}, \ldots, P_{\beta}^{(K)}\}$ form an $K$-dimensional orthonormal system, the $M^2 \times N^2$ light transport matrix $T_{\alpha|\beta}$ is determined by,

\begin{equation}
T_{\alpha|\beta} = \hat{C}_{\alpha|\beta} P_{\beta}^T, \quad (2)
\end{equation}

\begin{equation}
\hat{C}_{\alpha|\beta} = \begin{bmatrix} C_{\alpha|\beta}^{(1)} & C_{\alpha|\beta}^{(2)} & \cdots & C_{\alpha|\beta}^{(K)} \end{bmatrix}, \quad (3)
\end{equation}

\begin{equation}
P_{\beta} = \begin{bmatrix} P_{\beta}^{(1)} & P_{\beta}^{(2)} & \cdots & P_{\beta}^{(K)} \end{bmatrix}, \quad (4)
\end{equation}

where we use $K$-sets of projector illumination and the corresponding camera response [26]. Since the projector illumination vectors have $(P_{\beta}^{(1)})^T P_{\beta}^{(i)} = \delta_{ij}$, where $\delta_{ij}$ indicates the Kronecker delta, we can extract the $k$-th camera response vector $C_{\alpha|\beta}^{(k)}$, which corresponds to projector vector $P_{\beta}^{(k)}$, from matrix $T_{\alpha|\beta}$ by computing,

\begin{equation}
C_{\alpha|\beta}^{(k)} = T_{\alpha|\beta}^T P_{\beta}^{(k)}. \quad (5)
\end{equation}

All illumination vectors $\{P_{\beta}^{(1)}, P_{\beta}^{(2)}, \ldots, P_{\beta}^{(K)}\}$ satisfy Eq. (5).

As BFS uses the projector illuminations with $K = N^2$, all of the diagonal elements in matrix $P_{\beta}$ are unity, i.e. matrix $P_{\beta}$ is an $N^2 \times N^2$ identity matrix. The low-rank matrix approximation [21] employs $N^2 \times K$ matrix $P_{\beta}$, $K \ll N^2$; its column vectors span a Krylov subspace which are obtained by using Arnoldi’s method [30]. Since we obtain each camera response $C_{\alpha|\beta}^{(k)}$ by capturing projector illumination $P_{\beta}^{(k)}$, acquisition of the light transport matrix is virtually equal to designing projector illuminations to ensure that projector vectors $P_{\beta}^{(1)}, P_{\beta}^{(2)}, \ldots, P_{\beta}^{(K)}$, $\beta \in \{r, g, b\}$ span an orthonormal system. In this paper, we call the set of projector illuminations “orthogonal illumination”. We can represent arbitrary $N^2 \times N^2$-dimensional illumination vector $P_{\beta}$ by using the orthonormal basis: $\{P_{\beta}^{(1)}, P_{\beta}^{(2)}, \ldots, P_{\beta}^{(K)}\}$. According to Eq. (1), adding ambient light component $F_a$ to the matrix-vector product $T_{\alpha|\beta} P_{\beta}$ yields relighting vector $C_{\alpha|\beta}$ based on projector vector $P_{\beta}$.

3. Proposed Method

3.1 Design of Orthogonal Illumination

We focus on the Walsh-Hadamard matrix to design orthogonal illumination that forms an orthonormal system. It is well known that the Walsh-Hadamard matrix is a symmetric matrix whose entries are either $+1$ or $-1$ and whose rows (or columns) are mutually orthogonal. We consider that an arbitrary image used in relighting is decomposed uniquely by orthonormal basis. If the image transformation for relighting is based on the Walsh-Hadamard matrix, the decomposition computation involves only addition and subtraction, which correspond to sign $+1$ and sign $-1$ in the matrix, respectively. Compared to other orthogonal transforms, e.g. Fourier transform, discrete cosine transform, the Walsh-Hadamard matrix realizes high-speed image transformation processing for relighting. Moreover, since all entries of the Walsh-Hadamard matrix are zero, the projector illumination patterns generated according to the matrix elements yield sufficient light intensity; this leads to acquiring dense light transports related to global reflection light radiated from the entire environment.

According to Sylvester’s construction, the Hadamard matrix is given by

\[ H_1 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, \quad H_n = \begin{bmatrix} H_{n-1} & -H_{n-1} \\ H_{n-1} & H_{n-1} \end{bmatrix}, \quad (n \geq 2), \quad (6) \]

and matrix $H_n$, $(n \geq 1)$ is a symmetric matrix of $2^n$ rows and columns. We can easily implement Sylvester’s algorithm given by Eq. (6) on a personal computer. Obviously, the set of column vectors or row vectors represents an orthogonal system.\footnote{The illumination patterns designed in [24] are also based on a Hadamard matrix, unfortunately, they do not form the orthogonal system which Eqs. (2) – (4) demand.} We have the following Walsh-Hadamard matrix,

\[ W_n = \begin{bmatrix} h_1 & h_2 & \cdots & h_L \\ L = 2^n \end{bmatrix}, \quad (7) \]

by sorting column vectors in matrix $H_n$ according to the number of zero-crossings (sign inversions) from positive to negative or vice versa. Vector $h_1$ has no zero-crossings, i.e. all elements are 1, and the number of zero-crossings in vector $h_L$ is $L - 1$. The product of the $i$-th column vector $h_i$ and the transposition of the $j$-th column vector $h_j$ in matrix $W_n$ yields the $L \times L$ matrix $P_k$ as follows,

\[ P_k = h_i h_j^T, \quad (8) \]

where $k = L(i - 1) + j$.

Our proposed method applies matrix $P_k$ to the generation of orthogonal illumination. Given $N \times N = 2^n \times 2^n$ pixels on the projector plane in Fig. 1, we assign each element
in matrix $P_k$ to $2^l \times 2^l$ actual projector pixels, which have neither gap nor overlap, in the system, where $m = n + l$. The pixel assignment with $l = 0$ generates orthogonal illumination that has a 2D pattern with finest resolution, and it would be ideal in system setup to acquire detailed light transports from 3D structures. As pointed out in [15], such illumination patterns fail to acquire sufficient light transports in real environments due to limited dynamic range, image resolution, and projector/camera setting in the system etc. After adequately setting optical parameters at a level that does not saturate the entire camera response to effect projection-based displays, we determine a suitable value of $l$ to generate orthogonal illumination while considering the performance of the system. According to system performance, we generate $L^2$ projector illumination images from all matrices $P_k$, $k \in \{1, 2, \cdots, L^2\}$, of which each element is assigned to $2^l \times 2^l$ pixels on the illumination images. By reshaping matrix $P_k$ as a column vector and normalizing the vector, we have the $L^2$-dimensional vector $P^{(k)}_\beta$. The set of the $L^2$-dimensional vectors: $(P^{(1)}_\beta, P^{(2)}_\beta, \cdots, P^{(L^2)}_\beta)$ represents an orthonormal system. As we can employ in common the shaping matrix $\hat{L}$ signed to 2, some examples of orthogonal illuminations and camera responses with positive and negative components are shown in Figs. 2(a) and 2(b). We summarize here a processing flow that acquires positive and negative camera response images by using orthogonal illumination:

(i) Given $L \times L$ Hadamard matrix $H_n$, $(L = 2^n)$ by using Eq. (6), get Walsh-Hadamard matrix $W_n$ by sorting column vectors in matrix $H_n$ according to the number of zero-crossings.

(ii) From all combinations of the $i$-th column vector $h_i$ and the $j$-th column vector $h_j$ in Eq. (7), compute the $L \times L$ matrix $P_k$ by using Eq. (8), where $k = L(i - 1) + j$.

(iii) Generate $L^2$-sets of positive and negative illumination images from matrix $P_k$, $k \in \{1, 2, \cdots, L^2\}$; each element in matrix $P_k$ corresponds to $2^l \times 2^l$ pixels on the

The projector-camera system yields positive response vector $C^{(k)}_{\alpha\beta+}$ and negative response vector $C^{(k)}_{\alpha\beta-}$ by individually projecting positive illumination vector $P^{(k)}_{\beta+}$ and negative illumination vector $P^{(k)}_{\beta-}$ onto 3D objects. Figure 2(b) provides the positive and negative camera response images, which are obtained from scene B in Fig. 3(b). According to Eqs. (1) and (9), we have

$$C^{(k)}_{\alpha\beta+} - C^{(k)}_{\alpha\beta-} = T_{\alpha\beta+} P^{(k)}_{\beta+} + F_{\alpha+} - (T_{\alpha\beta-} P^{(k)}_{\beta-} + F_{\alpha-}) = T_{\alpha\beta+} P^{(k)}_{\beta+},$$

(12)

by calculating the difference between positive and negative response vectors [21]. From Eqs. (5) and (12), the difference between positive and negative response vectors yields proper camera response vector $C^{(1)}_{\alpha\beta-}$ that corresponds to projector illumination vector $P^{(k)}_{\beta-}$. Note that this difference calculation removes the ambient light component from the actual camera response. Obviously, as the first negative response vector $C^{(1)}_{\alpha\beta-}$ has only ambient light vector $F_{\alpha-}$, Eq. (12) holds for any sequential number $k \in \{1, 2, \cdots, L^2\}$.

We summarize here a processing flow that acquires positive and negative camera response images by using orthogonal illumination:

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(iii) Generate $L^2$-sets of positive and negative illumination images from matrix $P_k$, $k \in \{1, 2, \cdots, L^2\}$; each element in matrix $P_k$ corresponds to $2^l \times 2^l$ pixels on the
illumination image.

(iv) Output the illumination images from β-channel in the projector, and capture positive and negative response images by the camera in the sequence.

(v) By repeating step (iv) for individual projector channels $\beta \in \{r,g,b\}$, sequentially store positive and negative response images.

As our method uses $2L^2$ positive/negative illumination images for each channel, the system preserves a total of $6L^2$ positive/negative camera response images.

By reshaping the positive/negative camera response images as a column vector, we obtain positive response vector $C_{a\beta}^{(k)}$ and negative response vector $C_{a\beta}^{(k)}$ for all indexes $k \in \{1, 2, \ldots, L^2\}$. Next, we insert sequentially the difference response vector $C_{a\beta}^{(k)} = C_{a\beta}^{(k)} - C_{a\beta}^{(k)}$ into the $k$-th column of camera response matrix $\hat{C}_{a\beta}$ given by Eq. (3). According to Eq. (2), we obtain light transport matrix $T_{a\beta}$ from the camera response matrix $\hat{C}_{a\beta}$ and above-mentioned projector illumination matrix $\hat{P}_\beta$. Since the orthogonal illumination based on Walsh-Hadamard matrix uses a 2D plane light source, Eq. (2) yields matrix $T_{a\beta}$ that is composed of dense light transports.

3.3 Relighting Computation Using Light Transports

We detail a relighting computation made possible by the light transports. We assume that the relighting image is given by the $3M^2$-dimensional vector $[C_r, C_g, C_b]^T$, where $C_r$, $C_g$, and $C_b$ correspond to the r-, g-, and b-channel’s camera responses, respectively. Given the $3L^2$-dimensional projector vector $[P_r, P_g, P_b]^T$, we have

$$
\begin{bmatrix}
C_r \\ C_g \\ C_b
\end{bmatrix} =
\begin{bmatrix}
C_{rr} & C_{rg} & C_{rb} \\ C_{gr} & C_{gg} & C_{gb} \\ C_{br} & C_{bg} & C_{bb}
\end{bmatrix}
\begin{bmatrix}
P_r^T & 0 & 0 \\ 0 & P_g^T & 0 \\ 0 & 0 & P_b^T
\end{bmatrix}
\begin{bmatrix}
P_r \\ P_g \\ P_b
\end{bmatrix}
+ 
\begin{bmatrix}
F_r \\ F_g \\ F_b
\end{bmatrix},
$$

(13)

according to Eqs. (1) and (2). The relighting computation of Eq. (13) may demand huge working memory to handle all camera response matrices $\hat{C}_{a\beta}$, $\alpha, \beta \in \{r,g,b\}$ simultaneously.

Instead of the straightforward computation, we focus on the projector illumination matrix, which is composed of each channel’s orthogonal illumination, shown in the right-hand side of Eq. (13). We obtain each $L^2$-dimensional illumination vector

$$
Q_\beta = \hat{P}_\beta^T P_\beta, \quad \beta \in \{r,g,b\},
$$

(14)

by multiplying $L^2 \times L^2$ matrix $\hat{P}_\beta^T$ by input projector vector $P_\beta$. Since each column vector in matrix $P_\beta$ represents sequential orthogonal illumination vectors based on the Walsh-Hadamard matrix, Eq. (14) transforms input vector $P_\beta$ into projective vector $Q_\beta$ by using an orthonormal illumination basis: $[P_\beta^{(1)}, P_\beta^{(2)}, \ldots, P_\beta^{(L^2)}]$. Here, we assume that the $L^2$-dimensional vector $Q_\beta$ is given by $Q_\beta = [q_\beta^{(1)}, q_\beta^{(2)}, \ldots, q_\beta^{(L^2)}]^T$. If the $k$-th component $q_\beta^{(k)}$ is zero, column vectors $C_{a\beta}^{(k)}$ in matrix $\hat{C}_{a\beta}$, $\alpha \in \{r,g,b\}$ do not contribute anything to relighting computation using Eq. (13). Namely, we need not to load $C_{a\beta}^{(k)}$ in matrix $\hat{C}_{a\beta}$ for the relighting computation. By setting a threshold $y$ in Eq. (14), we can drop faint components that are close to zero.

Our method excludes the faint components which satisfy $|q_\beta^{(k)}| < y$ in projective vector $Q_\beta$ and so constructs compressed camera response matrices $\hat{C}_{a\beta}$, $\alpha \in \{r,g,b\}$ by collecting camera response vectors $C_{a\beta}^{(k)}$ that satisfy $|q_\beta^{(k)}| \geq y$. When the $K_\beta$-set of camera response vectors for $\beta$-channel is effective in Eq. (13), the rank of matrix $\hat{C}_{a\beta}$ is $K_\beta$; matrix $\hat{C}_{a\beta}$ is compressed to an $M^2 \times K_\beta$ matrix. Then, by sequentially operating matrix $\hat{C}_{a\beta}$, we obtain the $M^2$-dimensional camera response vector $C_{a\beta} = \hat{C}_{a\beta} Q_\beta$. The summation of all $M^2$-dimensional vectors $C_{a\beta}$, $\alpha, \beta \in \{r,g,b\}$ and ambient light vector $[F_r, F_g, F_b]^T$ yields the relighting image $[C_r, C_g, C_b]^T$ under the given projector illumination. Our key point is similar to wavelet lighting approximation for real-time rendering [8], which is restricted to relighting by using environment map. Even if users employ other projector illuminations that satisfy the requirements of an orthonormal system in Eq. (4), our approach can construct a compressed light transport matrix by using the sets of the projector illumination and the corresponding camera response for relighting computation.

4. Experiments and Results

4.1 Experimental System Setup

Figure 3(a) shows two experimental system configurations. These systems consist of an LCD projector (SONY VPL-FX41) and an IEEE1394b camera (Point Grey GRAS-50SSC-C) controlled by separate computers. Since the camera response exhibited almost linear functions relative to input brightness in each color channel, we measured the color channel’s luminance from the projector light by installing a spectroradiometer (PR655 SpectraScan). Based on the inverse response functions, the projector outputs a linearized response subject to input brightness so the system offers linear input/output responses [3], [31]. Figure 3(b) shows the 3D objects: plastic boxes, a gypsum torso, an accordion folded paper, a plastic bottle with water, a wineglass, a miniature, and a concave bowl made of styrene foam. The region of 256 × 256 pixels used in projector illumination is marked by the green frame, and the region of 500 × 500 pixels detected as camera response is marked by the red frame in Fig. 3(b).

We examined the system’s performance by observing the camera response using BFS while varying the distance between the system and the planar screen shown in Fig. 3(a). On the assumption that the projector and the camera are integrated, BFS with single pixel and $2 \times 2$ pixels did not yield
any camera response in the experiment due to the weak illumination light. A preliminary experiment confirmed that BFS with $3 \times 3$ pixels and $4 \times 4$ pixels allowed the detection of camera responses with no defective pixel within the range of $1.0-1.5$ m and the range of $1.5-3.5$ m, respectively. When the projector illuminated the object at the distance of 0.9 m, strong black offset lights from the projector appeared in the observed image, and BFS with $3 \times 3$ pixels exhibited unstable responses for each projector illumination. The system detected few black offset lights at the distance of about 1.5 m. In the range of $3.5-6.0$ m (the size limitation of our laboratory), BFS needed $5 \times 5$ pixels as light source to stably detect the camera responses. However, we found that the global reflection lights weakened gradually in the camera images when the above $256 \times 256$ projector pixels were illuminated from distances in excess of $5.0$ m. Given these conditions, we determined that the system works well in obtaining adequate direct and global light transports within the range of $1.5-5.0$ m in our environment.

In Fig. 3(a), the distance from the screen to the projector was about $2.8$ m in the left configuration and about $2.3$ m in the right configuration. In subsequent experiments, we empirically assign each element in matrix $P_k$ to $2^2 \times 2^2$ projector pixels ($l = 2$) that have neither gap nor overlap and generate an illumination image sequence. The positive/negative illumination images have pixel values of 0 and 255 which correspond to zero and non-zero elements in matrix $P_k$. According to our processing flow, once the positive/negative illumination images are sequentially output from the projector, our system captures the camera response images. Our orthogonal illumination demands 4,096 positive and 4,096 negative camera images per color channel to obtain all light transports from each 3D object.

4.2 Comparison with Color Crosstalk

We assume that our projector-camera system has the property of color crosstalk between the projector’s and camera’s channels. In this subsection, we examine the impact of this color crosstalk. We also demonstrate BFS with $4 \times 4$ pixels and push broom-type scanning (PBS) with a width of 4 pixels [26], for comparisons with our proposal. The system outputs individually color illumination from $\beta$-channel, $\beta \in \{r, g, b\}$, in the projector, and it sequentially captures the corresponding camera responses for each color illumination.
according to each method.

We conduct a relighting test by using an image with color bar code. From the left to the right, the RGB values (R,G,B) are (150,150,150), (100,150,100), (150,100,100), and (100,100,150). In Fig. 4, we show relighting images yielded by each method with crosstalk: the first, the second, and third rows correspond to BFS, PBS, and our orthogonal illumination. As our method used the threshold of $\gamma = 1 \times 10^{-3}$ in the relighting computation, the rank of each light transport matrix was equal to $K_r = K_g = K_b = 2$. The fourth row in Fig. 4 shows the actual observed images, in which each 3D object was illuminated with color bar code image. For reference, Fig. 5 shows direct and global components, which are reflected from the 3D objects, separated by using the multiplexed illumination method [32]. We found that the actual images have weak and widely distributed global reflection lights, as shown in Fig. 5(b). See the global lights around the chest in scene A, in the interior of plastic box and on the lower half part of the plastic bottle in scene B. BFS and PBS did not reproduce these global reflection lights, while our method accurately reproduced them. Although we carefully adjusted the camera’s optical settings within the limited dynamic range of the camera’s response sensitivity, BFS and PBS yielded somewhat insufficient relighting images. Compared to the actual camera images, our method reproduced virtually the same color bar code image. From the left to the right, the RGB values in the relighting images shown in Fig. 4. We found a remarkable visual difference between light transports with color crosstalk and without color crosstalk. In our system, we confirmed that the camera responses detected by handling white illumination includes both the light transports between the same channels ($\alpha = \beta$) and the light transports between other channels ($\alpha \neq \beta$). In this case, since the light transport matrices: $T_{rr}$, $T_{gg}$, and $T_{bb}$ neglected the proper correspondences between the projector’s channels and camera’s channels in the system, i.e. color crosstalk, they could not replicate the relighting images yielded by the actual system. These results determine that color crosstalk between projector pixels and camera pixels is an important factor in our system.

4.3 Dimensional Compression

This subsection demonstrates the dimensional compression attained by our method with threshold $\gamma$. Figure 7 shows the illumination images used in the relighting experiments. By using Eq. (14), we compute the $L^2$-dimensional illumination vectors $Q_r$, $Q_g$, and $Q_b$ from these test images. Given a threshold $\gamma$, we retain the vector components that satisfy $|q_{\alpha}^{(k)}| \geq \gamma$ and replace the faint vector components that have $|q_{\alpha}^{(k)}| < \gamma$ by zero in each $\beta$-channel illumination vector. When we retain the non-zero vector components, whose number is $K_\beta < L^2$, we obtain compressed light transport matrix $T_{\alpha}^{(k)}$, $\alpha \in \{r,g,b\}$; its rank is $K_\beta$. Table 1 summarizes the effective ranks $K_r$, $K_g$, and $K_b$ of the light transport matrices, when setting $\gamma = 1 \times 10^{-2}$, $1 \times 10^{-3}$, and $1 \times 10^{-4}$. As illumination #1 is composed of tiled color patterns, each light transport matrix is drastically compressed into a low-rank matrix. Compare illumination #3 and illumination #4, which has multiple color point lights. Although we found noticeable differences in the compressed dimension at $\gamma = 1 \times 10^{-2}$, we obtained light transport matrices of similar rank to those determined with $\gamma = 1 \times 10^{-3}$.
Fig. 8 Vector components obtained from illumination #3.

Table 1 Effective ranks estimated by threshold $\gamma$.

| Image | $\gamma = 1 \times 10^{-2}$ | $\gamma = 1 \times 10^{-3}$ | $\gamma = 1 \times 10^{-4}$ |
|-------|-----------------------------|-----------------------------|-----------------------------|
|       | $K_r, K_g, K_b$             | $K_r, K_g, K_b$             | $K_r, K_g, K_b$             |
| #1    | 18, 18, 18                  | 27, 27, 27                  | 300, 296, 299               |
| #2    | 101, 122, 98                | 2244, 2232, 2152            | 3877, 3889, 3851            |
| #4    | 668, 720, 712               | 2092, 2124, 2360            | 3050, 3064, 3620            |
| #5    | 474, 473, 417               | 1174, 1152, 1134            | 2758, 2784, 2712            |
| #6    | 677, 465, 657               | 3373, 3250, 3408            | 4031, 4017, 4027            |

larly, the ranks of light transport matrices used in illumination #2 approach those obtained from illumination #5 which includes concentric color patterns, at $\gamma = 1 \times 10^{-3}$. From illumination #2 to illumination #5, light transport matrices used in relighting with $\gamma = 1 \times 10^{-3}$ generally compressed the original light transport matrices by the compression rate of 50% to 75%. For illumination #6, which is composed of alphanumeric characters, our method with $\gamma = 1 \times 10^{-3}$ achieved the compression rate of 25%. On the assumption that vector components that satisfy $|q^{(k)}_\beta| \geq 1 \times 10^{-4}$ are acceptable in relighting computation, the ranks of light transport matrices yielded from illuminations #4 and #5 exhibit the compression rate of 25% while those yielded from illuminations #2, #3, and #6 approach to full rank.

Figure 8 and Fig. 9 illustrate the vector components obtained from illuminations #3 and #5, respectively. The vertical axis plots component value $q^{(k)}_\beta$. The upper row of each figure shows the effective illumination vector components obtained by thresholds $\gamma = 1 \times 10^{-2}$, $1 \times 10^{-3}$, and $1 \times 10^{-4}$, and the lower row shows close-ups of the illumination vector components delineated by dashed-lines in the upper row. In Fig. 8, the major components are concentrated in the low frequency domain and the illumination components weaken gradually as $k$ increases. In contrast, Fig. 9 exhibits periodic illumination components at a regular interval from low to high frequency domains. Although the high frequency components in Fig. 8 are completely eliminated by using $\gamma = 1 \times 10^{-2}$, those in Fig. 9 remain as periodic illumination components in the high frequency domain. Beyond threshold $\gamma = 1 \times 10^{-3}$, the faint components extracted from illumination #3 are visible in the high frequency domain. In Fig. 9, we found that gaps between one periodic component and the next periodic component are empty when $\gamma = 1 \times 10^{-2}$, and that the faint components obtained by threshold $\gamma = 1 \times 10^{-3}$ or $1 \times 10^{-4}$ occupy the gaps. In order to examine the effect of the faint components that occupy the gaps in illumination image, we recomputed the projector illumination vector $P^\beta$ by multiplying the projective vector $Q^\beta$ with Walsh-Hadamard matrix $P^\beta$, i.e. $P^\beta = P^\beta Q^\beta$, $\beta \in \{r, g, b\}$, according to Eq. (14). Figure 10 shows the illumination images recovered from the projector vectors $P^r$, $P^g$, and $P^b$ where we enlarged each image to emphasize the visual differences. Both images faithfully reproduce the original concentric color patterns. However, in the image yielded by threshold $\gamma = 1 \times 10^{-2}$, undesirable color dot patterns appear in not only the center of the concentric circle but also pixel regions other than the concentric circle. We found that the faint illumination components between $\gamma = 1 \times 10^{-3}$ and $\gamma = 1 \times 10^{-2}$ are important in preventing the deterioration of image quality.

Given illumination images #1 ~ #6 for scene A, scene B, and scene C, we conduct relighting simulations by using Eq. (13) with $\gamma$ in order to determine the proper value of $\gamma$. 

Given illumination images #1 ~ #6 for scene A, scene B, and scene C, we conduct relighting simulations by using Eq. (13) with $\gamma$ in order to determine the proper value of $\gamma$. 

We assume that the relighting images estimated by Eq. (13) with $\gamma = 0$, which yields full rank light transport matrix, are ground truth in this experiment. For each color channel, we evaluate the RMS error between the ground truth and the relighting image yielded by using threshold $\gamma$; the results are summarized in Table 2, Table 3, and Table 4. Relighting with $\gamma = 1 \times 10^{-2}$ yielded remarkable errors except for illumination #1. We demonstrated that relighting with $\gamma = 1 \times 10^{-3}$ yields accurate relighting images, in which the RMS errors for each color channel are suppressed to about one level, and that all relighting images obtained by using $\gamma = 1 \times 10^{-4}$ are virtually equal to those by using a full rank light transport matrix. It is conceivable that the relighting images with $\gamma \leq 1 \times 10^{-3}$ are almost the same, visually, as those estimated by the full rank light transport matrix; the reader can confirm this in the next subsection. Based on these results, we heuristically determined that $\gamma = 1 \times 10^{-3}$ is the suitable threshold for ensuring accurate relighting im-

Table 2  \textbf{RMS errors yielded for scene A.} [unit: level]

| Image | $\gamma = 1 \times 10^{-2}$ | $\gamma = 1 \times 10^{-3}$ | $\gamma = 1 \times 10^{-4}$ |
|-------|----------------------------|----------------------------|----------------------------|
|       | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ |
| #1    | 0.5, 0.7, 0.7 | 0.4, 0.4, 0.4 | 0.1, 0.1, 0.1 |
| #2    | 9.4, 10.2, 9.2 | 1.4, 1.6, 1.5 | 0.1, 0.1, 0.1 |
| #3    | 11.0, 12.3, 12.6 | 0.9, 1.1, 1.2 | 0.1, 0.1, 0.1 |
| #4    | 6.7, 7.6, 8.2 | 0.5, 0.7, 0.7 | 0.1, 0.1, 0.1 |
| #5    | 4.9, 5.9, 6.2 | 0.9, 1.0, 0.9 | 0.1, 0.2, 0.1 |
| #6    | 11.2, 13.0, 12.0 | 0.6, 0.8, 0.7 | 0.1, 0.1, 0.1 |

Table 3  \textbf{RMS errors yielded for scene B.} [unit: level]

| Image | $\gamma = 1 \times 10^{-2}$ | $\gamma = 1 \times 10^{-3}$ | $\gamma = 1 \times 10^{-4}$ |
|-------|----------------------------|----------------------------|----------------------------|
|       | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ |
| #1    | 0.5, 0.6, 0.6 | 0.4, 0.3, 0.4 | 0.1, 0.1, 0.1 |
| #2    | 8.4, 9.4, 8.3 | 1.1, 1.5, 1.4 | 0.1, 0.1, 0.1 |
| #3    | 10.2, 10.7, 11.2 | 0.8, 1.0, 1.1 | 0.1, 0.1, 0.1 |
| #4    | 6.3, 7.9, 8.2 | 0.5, 0.8, 0.7 | 0.1, 0.1, 0.1 |
| #5    | 4.7, 5.5, 5.7 | 0.7, 0.8, 0.8 | 0.1, 0.2, 0.1 |
| #6    | 10.3, 11.2, 10.7 | 0.6, 0.7, 0.7 | 0.1, 0.1, 0.1 |

Table 4  \textbf{RMS errors yielded for scene C.} [unit: level]

| Image | $\gamma = 1 \times 10^{-2}$ | $\gamma = 1 \times 10^{-3}$ | $\gamma = 1 \times 10^{-4}$ |
|-------|----------------------------|----------------------------|----------------------------|
|       | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ | $\Delta r, \Delta g, \Delta b$ |
| #1    | 0.2, 0.2, 0.2 | 0.2, 0.2, 0.2 | 0.1, 0.1, 0.1 |
| #2    | 2.7, 3.3, 3.1 | 0.4, 0.4, 0.4 | 0.1, 0.1, 0.1 |
| #3    | 3.2, 4.2, 3.6 | 0.3, 0.4, 0.4 | 0.1, 0.1, 0.1 |
| #4    | 1.6, 3.2, 3.3 | 0.2, 0.2, 0.2 | 0.0, 0.1, 0.1 |
| #5    | 1.4, 1.9, 2.1 | 0.3, 0.4, 0.4 | 0.1, 0.1, 0.1 |
| #6    | 2.9, 4.1, 3.6 | 0.2, 0.3, 0.3 | 0.0, 0.0, 0.0 |
Fig. 11  Relighting images yielded by BFS.

Fig. 12  Relighting images yielded by PBS.

4.4 Relighting

Figure 11 and Fig. 12 show relighting examples yielded by BFS and PBS, respectively. Figure 13 shows relighting examples created by our method with $\gamma = 1 \times 10^{-3}$; the light transport matrices have rank compressed to $K_\beta$, $\beta \in \{r, g, b\}$, see Table 1. Figure 14 displays the actual images observed by our experimental system as the benchmark. Comparison with actual images shows that BFS yielded rough textures and colors that were different from the actual products. Obviously, BFS reproduced dark relighting images.
without global reflection lights and did not yield the gloss of the plastic bottle and shining wineglass in these relighting images. In scene C, since the illumination light irradiated from each light source diffused isotropically within the interior of the concave bowl, the indirect reflection light was weakened so that BFS could not measure the feeble camera response, which was buried in image noise. Although PBS partly improved the texture and color compared to BFS, it also could not yield accurate global reflection lights in the relighting images according to each environment. In contrast, our method provided excellent relighting images that compare favorably with the actual camera images, on each 3D structure. Our relighting method accurately reproduces the tiled pattern of illumination #1 onto each scene and realistically simulates photographic images by using illuminations #2 and #3. For illumination #4, the compressed light
transport matrix reproduces the good relighting image under spotlight sources. The relighting image created with illumination #5 faithfully recreates the concentric rings on the plastic bottle with water and the wineglass. We confirmed that the relighting image based on illumination #6 precisely replicates the alphanumeric characters reflected from the interior and exterior of the plastic boxes and so follows the actual camera image.

To evaluate the validity of the relighting by using the compressed light transport matrix, Fig. 15 shows the relighting images computed by our method with \( \gamma = 1 \times 10^{-2}, \ 1 \times 10^{-3}, \) and \( \gamma = 0 \) (full rank). Although relighting with \( \gamma = 1 \times 10^{-2} \) offers rough texture and concentric rings with noisy patterns, both relighting with \( \gamma = 1 \times 10^{-4} \) and that in Fig. 13 are visually identical to those yielded by the full rank matrix. We estimate the cost of relighting computations using the compressed light transport matrix. Note that the \( \alpha \)-channel’s camera response vector that constructs a relighting image is given by \( \hat{C}_{\alpha\beta} = C_{\alpha\beta}Q_{\beta} \), where \( \hat{C}_{\alpha\beta} \) is compressed to the \( M^2 \times K_{\beta} \) matrix and \( Q_{\beta} \) is the \( \beta \)-channel’s projective vector yielded by Eq. (14). As the computation of multiplications and additions in the matrix-vector product, \( \hat{C}_{\alpha\beta}Q_{\beta} \), is identical to \( M^2(2K_{\beta} - 1) \) arithmetic operations, the total computation cost for \( \alpha, \beta \in \{r, g, b\} \) is estimated to be \( 6M^2(K_r + K_g + K_b - 1) \) arithmetic operations, which include the cost of adding the ambient light vector. In the case of a full rank light transport matrix, Eq. (13) carries out relighting computation and the total cost for \( \alpha, \beta \in \{r, g, b\} \) is estimated to be \( 6M^2(3L^2 - 1) \) arithmetic operations.

Here, we give the ratio of the computation cost of relighting yielded by the dimensional compression to relighting with full rank by \( (K_r + K_g + K_b - 1)/(3L^2 - 1) \). In Table 5, we provide the computation cost ratio for relighting yielded by the compressed light transport matrices, when setting \( \gamma = 1 \times 10^{-2}, \ 1 \times 10^{-3}, \) and \( 1 \times 10^{-4} \). Relighting with \( \gamma = 1 \times 10^{-2} \) yielded very low computation cost ratio for illumination #3 and the low cost ratio of about 1/10 for illumination #5; unfortunately, it yielded relighting images with low image quality in Fig. 15. We found that relighting using \( \gamma = 1 \times 10^{-3} \) has computation cost ratios of almost 1/2 for illumination #3, 1/3 for illumination #5, respectively. The dimensional compression offered by Eq. (14) with \( \gamma = 1 \times 10^{-3} \) clearly enhances the relighting computation while keeping the quality of the relighting images high. Although relighting with \( \gamma = 1 \times 10^{-4} \) recreated high quality relighting images, see Fig. 15, its computation cost ratio of illumination #3 is close to relighting using the full rank light transport matrix and that of illumination #5 is estimated to be almost 2/3. For illumination #6, the dimensional compression using \( \gamma = 1 \times 10^{-4} \) only slightly impacts the relighting computation as shown in Table 5; its processing virtually replicates the full rank version. The effective ranks \( K_\beta, \beta \in \{r, g, b\} \) of the light transport matrix are determined by projective vectors \( Q_{\beta} \) computed by Eq. (14) and acceptable threshold \( \gamma \). Given a suitable threshold, e.g. \( \gamma = 1 \times 10^{-3} \), the compressed light transport matrix is very useful for lowering the cost of relighting computation.

For enhanced relighting applications, we provide composite relighting based on two illumination images. We denote the illumination vectors obtained from illumination #a and illumination #b, \( a, b \in \{1, 2, \ldots, 6\} \) by the \( 3L^2 \)-dimensional vectors \( P_a \) and \( P_b \), respectively. Given any real constants \( \lambda_a \) and \( \lambda_b \), we create composite illumination by using \( P = \lambda_a P_a + \lambda_b P_b \). By substituting the normalized illumination vector into Eq. (14), we calculate the projective illumination.

| Image | \( \gamma = 1 \times 10^{-2} \) | \( \gamma = 1 \times 10^{-3} \) | \( \gamma = 1 \times 10^{-4} \) |
|-------|-----------------|-----------------|-----------------|
| #1    | 0.0043          | 0.0065          | 0.0728          |
| #2    | 0.0092          | 0.3164          | 0.8961          |
| #3    | 0.0260          | 0.5394          | 0.9451          |
| #4    | 0.1708          | 0.5351          | 0.7921          |
| #5    | 0.1109          | 0.2815          | 0.6717          |
| #6    | 0.1447          | 0.8163          | 0.9827          |

Fig. 15 Relighting images yielded by our method with \( \gamma \).
llumination vector for each color channel, and then obtain the compressed light transport matrix by eliminating the vector components that satisfy $|q^{(k)}_j| < 1 \times 10^{-3}$; the final matrix yields the composite relighting image. Figure 16 demonstrates composite relighting from illuminations #2 and #5, and the composite relighting from illuminations #5 and #6. Logically, the linear combination of multiple illuminations yields various relighting images. Since Eqs. (13) and (14) handle relighting based on any illumination, we can apply the relighting computation to illumination design for projection mapping systems.

5. Conclusion

We proposed a practical method that acquires dense light transports from unknown 3D objects by employing orthogonal illumination based on a Walsh-Hadamard matrix. We introduced the color crosstalk between the projector’s and camera’s channels in the system, and described the light transport matrix by using sets of orthogonal illumination and the corresponding camera response. Our method handles not only direct reflection light with color mixing between projector pixels and camera pixels but also global light radiated from the entire environment. Given a projector illumination, our approach analyzes illumination components that are obtained uniquely by the orthogonal illumination basis, and constructs a compressed light transport matrix that includes the effective illumination components. We use the compressed light transport matrix to efficiently carry out the relighting computation.

We examined the impact of color crosstalk in our projector-camera system. We obtained light transports by using BFS, PBS, and our orthogonal illumination from some 3D objects, and reproduced relighting images by handling the light transports. The results demonstrated that orthogonal illumination is a more effective way of acquiring accurate light transports than the existing methods and showed that the relighting images with color crosstalk compare favorably with the real images observed by the system. Moreover, we conducted relighting computation with dimensional compression, and determined the effective rank of the light transport matrix that offers accurate relighting. Compressed light transport matrices provided excellent relighting images that are virtually identical to actual camera observations. We found that the dimensional compression with a suitable threshold clearly enhances the relighting computation while keeping the quality of the relighting images high. Thus, the compressed light transport matrix will be very useful in lowering the cost of the relighting computation as well as yielding accurate relighting images on various 3D structures.

Projection mapping systems demand illumination design in advance to ensure that they provide image displays with excellent presence. Since the proposed method accurately and flexibly acquires light transports regardless of the complexity of the actual environment, relighting simulations by using the light transports can support practical projection mapping systems. Our approach is not restricted to a Walsh-Hadamard matrix. Even if users employ other projector illuminations that satisfy the requirements of an orthonormal system, our approach can construct a compressed light transport matrix by using the sets of the projector illumination and the corresponded camera response for relighting computation. For the purpose of realizing high-resolution and large scale relighting, we will enhance the proposed method to acquire all light transports efficiently and perform prompt relighting simulations.

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