1000-9825/2002/13(04)0501-09 ©2002 Journal of Software 软 件 学 报 Vol.13, No.4

Object Image Synthesis under Changing of Illumination*

XU Dan[1], HENG Pheng-ann[2]

[1](*Deptartment of Computer Science and Engineering, Yunnan University, Kunming* 650091, *China*);

[2](*Deptartment of Computer Science and Engineering, Chinese University of Hong Kong, Hong Kong, China*)

E-mail: dannaxu@yahoo.com; pheng@cse.cuhk.edu.hk

Received March 1, 2001; accepted October 9, 2001

Abstract: Illumination is an important aspect in realistic graphics rendering and most image related applications. The paper proposes a pure image based rendering method to synthesis the variation of illumination impacted on an object. Rather than estimating the BRDF function or any parameters in a reflectance model, Singular Value Decomposition (SVD) is used to estimate a low dimensional approximation of the image set of a Lambertian object under both changing of illumination and geometrical pose. In the method, light directions are analytically derived from the samples and the base images as well as images with known of the class of the objects. Images with any novel lighting directions can be rendered very efficiently by properly linear combination of the base images. Smooth morphing sequence of lighting and pose variation can be generated by linear interpolation of the SVD coefficients. A feature of this method is that it supplies a simple and compact way to represent dataset and synthesize novel images, which lends it to be suitable for many image-based applications.

Key words: Lambertian model; singular value decomposition; illumination; image based rendering; image morphing

An object's appearance depends in large part on the way in which it is viewed. Often slight changes in pose and illumination produce large changes in an object's appearance. Recently, techniques related to synthesizing novel image from known images with different pose and view positions have been widely researched in both computer graphics and computer vision communities, which are known as image-based modeling and rendering (IBMR). However, most of the existing IBMR systems assume that illumination is static for scenes and objects. Very few works consider the variation of lighting[1~3], and they all try to explicitly recover the BRDF function or reflection model of an object. In fact, even if the pose and view point are fixed, appearance of an object depends on the properties of its surface and the illumination conditions at a certain time. Accurate estimation of all of these factors from images is extremely difficult, especially in the case that the surfaces contain specular reflections, complex interreflections and shadows. Therefore, it is essential for researchers to develop an efficient image-based method that can deal with the dynamic illumination. In other words, can we solve the problem of real-time rendering of novel images given the number of light sources and their directions without knowing 3D geometry and lighting

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* Supported by the Young Academic and Technical Leader Foundation of Yunnan Province of China under Grant No.2000YP20 (云南省中青年学术和技术带头人基金); Hong Kong Research Grant Council (RGC) Earmarked Research Grants under Grant No. CUHK4306/98E (香港研究资助局资助项目)

XU Dan was born in 1968. She is a professor at the Department of Computer Science and Engineering, Yunnan University. She received her Ph.D. degree in computer science from the University of Zhejiang in 1999. Her current research interests include image-based modeling and rendering, computer vision, image analysis, virtual reality and multimedia. **HENG Pheng-ann** received his Ph.D. degree from the Indiana University of USA in 1992. He is an associate professor at the Department of Computer Science and Engineering, the Chinese University of Hong Kong. His research interests include virtual reality applications in medicine, scientific visualization, 3D medical imaging, user interface, interactive graphics and animation.

model?

We notice that there have been some efforts in computer vision devoted to image variation produced by changes of illumination[4~7].Applications include recognition of human faces, real-time object recognition, tracking and position planning[8~11]. These methods advocate exploring alternative ways to represent all possible variations produced on an object appearance by changing of illumination. Though some methods considered recovering geometric models[10,12], most of these methods can be grouped into Appearance based Methods (ABMs), or image-based method in general. In ABMs, the appearances of objects are learnt by applying principal component analysis (PCA) to a representative dataset of images of an object. For convex and diffuse objects, PCA produces a low-dimensional subspace called illumination manifold[7], or eigenspace in some literature[5], which captures most of the variation of the dataset. In the case of recognition, a new image of the object was projected into the illumination manifold and the nearest matching point was found out in the low-dimensional space. These works are motivations of ours to develop a more efficient approach to synthesis lighting variation in a novel image rather than estimating the reflection model or BRDF directly in IBMR techniques.

In this paper, we assume that all objects are close to convex and Lambertian surface, which holds for many man-made and natural things. Also, we assume that light sources are located in the distance. We propose a light rendering method relies on a mathematical theory in linear algebra, called Singular Value Decomposition (SVD). With SVD decomposition, we can extract the principle components, or impact features involved in the dataset. For example, when we consider the influence of illumination changing impacted on an object with fixed pose, the principal components characterize the variances of photometric properties of the object. The important differences between our approaches and the previous vision applications are that: First, our destination is rendering a novel image under given specification of illumination, rather than matching a given image with images in the dataset or recognizing whether the given image is an image of a known object; Second, in our method, light directions and their relations with principal components have been expressed analytically and estimated optimally; Third, our approach deal with not only changes of illumination but also changes of object poses.

The rest of this paper is organized into five sections. Section 1 introduces simple linear reflection model. Section 2 introduces some computer vision theories related to our approach. Section 3 gives a summary about SVD decomposition and analyzes its physical interpretation in our applications. Section 4 discusses our algorithms that synthesize novel images and view morphing series under novel illumination and object pose settings. Section 5 shows some experimental results. The last two sections are conclusion and acknowledgement.

1 Linear Reflectance Model

The brightness of a Lambertian surface element illuminated by a point light source at infinity is

$$E(d,x)=s(d)\cdot B(x)\,, \tag{1}$$

where $B(x)=\rho(x)N(x)$ is the product of local surface albedo $\rho(x)$ with the local unit surface normal vector $N(x)$, x=1,2,…,n ranges over all pixels of the image. $s(d)$ in $\Re^3$ signifies the product of light source intensity with a unit vector of the lighting direction indexed by integer d. Simply, we name $s(d)$ as the lighting *property vector* and B(x) as the *surface property vector*. If light source intensity is constant, then $s(d)$ becomes to a variable only related to lighting direction.

In fact, all possible lighting directions can be normalized as a point on a unit spatial sphere, called *illumination sphere*. Thus, for a given light direction vector $\boldsymbol{s}$, we can represent it as a linear combination of any three linear independent base vectors $\boldsymbol{s}_1,\boldsymbol{s}_2,\boldsymbol{s}_3$ in the illumination sphere space, that is

$$\boldsymbol{s}=c_1\cdot\boldsymbol{s}_1+c_2\cdot\boldsymbol{s}_2+c_3\cdot\boldsymbol{s}_3=\sum_{i=1}^{3}c_i\cdot\boldsymbol{s}_i=\Phi\boldsymbol{S}\,, \tag{2}$$

where $\Phi=(c_1\ c_2\ c_3)$ is the combination coefficients, and $\boldsymbol{S}=[\boldsymbol{s}_1,\boldsymbol{s}_2,\boldsymbol{s}_3]$ is the matrix comprised of three base directions. Thus, given a light source direction in the illumination sphere space, the coefficients of combination can be calculated by

$$\Phi=\boldsymbol{s}\cdot\boldsymbol{S}^{-1}. \tag{3}$$

Assume that intensities of light sources are constant, and then substitute Eq.(2) for s in Eq.(1), we have

$$\boldsymbol{E}(x)=(c_1\cdot\boldsymbol{s}_1+c_2\cdot\boldsymbol{s}_2+c_3\cdot\boldsymbol{s}_3)\cdot\boldsymbol{B}(x).$$

If we denote $\boldsymbol{e}_i(x)=\boldsymbol{s}_i\cdot\boldsymbol{B}(x), i=1,2,3$, and $\Pi=[\boldsymbol{e}_1\quad\boldsymbol{e}_2\quad\boldsymbol{e}_3]$, then Eq.(1) can be rewritten as

$$\boldsymbol{E}(x)=c_1\boldsymbol{e}_1(x)+c_2\boldsymbol{e}_2(x)+c_3\boldsymbol{e}_3(x)=\Phi\Pi$$

which is the image brightness of a point under any light direction and it is combined by the same coefficients as that of the lighting direction is composed. Furthermore, if we consider all visible points on the surfaces, then a novel image can be expressed as

$$\boldsymbol{I}=\Phi\boldsymbol{B}, \tag{4}$$

where $\boldsymbol{B}=[\boldsymbol{b}_1\ \boldsymbol{b}_2\ \boldsymbol{b}_3]$ represents three base images account for three base illuminants.

Up to now, the first problem left is that whether the three base images span the whole image space of an object with fixed pose and changing of illumination, or only a subspace of it? The second problem left is how to find the base images as well as base lighting directions. If they are estimated, then any novel image can be generated via Eqs.(3) and (4).

2 Related Vision Studies

Recently studies in computer vision demonstrate that for an object with convex shape and Lambertian reflectance, the set of all images under an arbitrary combination of point light sources forms a convex polyhedral illumination manifold in the image space R_n where n is the number of pixels of images[7]. The illumination manifold is a low-dimensional linear subspace that characterizes the photometry of an object. More recently, an empirical investigation reported by Ref.[4] shows that for Lambertian surfaces of arbitrary texture, the entire illumination manifold could be constructed from just three images taken using known lighting properties. This means the dimensionality of the illumination manifold is three.

Considering that an object is simultaneously illuminated by m light sources at infinity, its image is given by the superposition of the images that would have been produced by the individual light sources.

$$\boldsymbol{E}(d,x)=\sum_{k=1}^{m}(\boldsymbol{s}_k(d)\cdot\boldsymbol{B}(x))=\sum_{k=1}^{m}\boldsymbol{s}_k(d)\cdot\boldsymbol{B}(x)=\tilde{\boldsymbol{s}}\boldsymbol{B}(x)$$

where $\tilde{\boldsymbol{S}}$ serves as a single effective source and is simply the average of individual source vectors.

In real world, no object is pure diffuse and convex surface. It contains more or less some specular, self-shadow components and noise, which leads to the dimensionality of the image space of the object increasing, so we can't find exactly three base images in practice, but more than that. The experimental results given by Epstein and Hallinan et al show that 5±2 eigenvalues are typically enough to account for most of the variation (up to 90% percentage of variation for face)[4,5]. These results mean that for each face we can approximate the image space by the first five principal components

$$\boldsymbol{I}=\sum_{i=1}^{5}c_i\boldsymbol{b}_i. \tag{5}$$

This conclusion can also be observed in our experiments. In fact, three base images have already covered over 90% variation for an object in our examples. Thus, conditions that the object must be convex and Lambertian surface can be weakly satisfied.

In Eq.(5), if the number of coefficients is set to be three then this will be similar to the ideal Lambertian linear model. It is conjectured in depth that the first three principal components of the linear subspace correspond to Lambertian illumination of the object and higher order principle components correspond to specularities and sharp shadows.

Also we find that, in Eq.(2), if Φ is constrained to be equal to the synthesized light direction s, then the base matrix S is equal to identity matrix, which means the three base directions are exactly along the three Cartesian coordinate axes. Thus, if the first three principal components correspond to the images lit from front/back, from left/right, and from above/bottom, then their related coefficients represent lighting direction. This is an important observation that will be used in Section 4.

So far, the question left is to find the best three principal components and corresponding coefficients. In the following sections, we will introduce methods that solve above problem in terms of least squared framework.

3 SVD Decomposition

Our way to solve this problem is using SVD decomposition. SVD has previous been applied to the related problem of photometric stereo by Hayakawa[13]. For Lambertian source with a single illumination, SVD allows one to estimate shape, albedo, and lighting conditions up to an unknown 3×3 constant matrix. Zhang proposed an SVD based method to model and render illumination variation of a scene[12]. This method, however, relies on a reconstructed geometry model and all the coefficients cannot be analytically derived and be related to the lighting direction.

If we denote each image as an n-element row vector, and then an image matrix is comprised of all sample images represented as row vectors. Denote $m\times n$ matrix $\boldsymbol{W}$ as the image matrix, where the number of rows m is the number of images in the dataset. SVD decomposition of $\boldsymbol{W}$ is then expressed as

$$\boldsymbol{W} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T \qquad (6)$$

where $\boldsymbol{\Sigma}$ is a diagonal matrix whose elements are the square roots of the eigenvalues of $\boldsymbol{W}\boldsymbol{W}^T$ (or equivalently of $\boldsymbol{W}^T\boldsymbol{W}$) sorted by $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$. λ_i is called singular values of $\boldsymbol{W}$. The columns of $\boldsymbol{U}$, denoted as $[\boldsymbol{u}_1|\boldsymbol{u}_2|\ldots|\boldsymbol{u}_n]$, correspond to the normalized eigenvactors of the matrix $\boldsymbol{W}^T\boldsymbol{W}$. The columns of matrix $\boldsymbol{V}$, denoted as $[\boldsymbol{v}_1|\boldsymbol{v}_2|\ldots|\boldsymbol{v}_n]$, correspond to the normalized eigenvactors of the matrix $\boldsymbol{W}\boldsymbol{W}^T$. They are in the same order as that of the singular values in $\boldsymbol{\Sigma}$. The corresponding eigenvactor $\boldsymbol{u}_i$ in $\boldsymbol{U}$ satisfying fundamental equation

$$\boldsymbol{W}^T\boldsymbol{W}\boldsymbol{u}_i = \lambda_i^2\boldsymbol{u}_i\ ,$$

where $\boldsymbol{u}_i \in \Re^n, \|\boldsymbol{u}_i\| = 1$. The term $\boldsymbol{u}_i$ is also called the principal singular direction associated with λ_i.

The principal singular directions imply the main changes involved in the image sequence. These changes may be geometrical or photometrical properties of the object.

4 Novel Image Synthesis and Animation

According to the vision theories described in Section 2, if the dimensionality of illumination manifold is three, then we will get exactly three non-zero singular values after executing SVD decomposition for image matrix W. However, in practice, we do not expect only three non-zero singular values in Σ because of the fact that we cannot get pure diffuse surface in the real world. There always exist some shadows, specularities, or noise in our data set.

Alternatively, we can always find optimized solution of three base images and coefficient vector such that the energy function

$$\sum_{x,d}\{\boldsymbol{E}(d,x) - \sum_{i=1}^{3} c_i(d)e_i(x)\}^2 = (\boldsymbol{W} - \boldsymbol{\Phi}\boldsymbol{B})^2 \qquad (7)$$

is minimal. In linear algebra theory, it can be proved that if a $m\times n$ matrix W has singular values $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$, and the rank of W is r ($r<n$), then for any $k<r$, a best rank k approximation to W is

$$\boldsymbol{W}^* = \sum_{i=1}^{k} \lambda_i \boldsymbol{u}_i \boldsymbol{v}_i^T .$$

Therefore, using SVD guarantees to give us the best least squared solution in any case and the biggest three singular values of Σ as well as the corresponding bases in matrixes U and V build an optimized approximation to the Lambertian part of the reflection model of the object. Let's denote the submatrix constitutes of the first three columns of U and V as F and G, respectively. Above theory enable us to use SVD to solve B and Φ up to a linear transformation.

$$\Phi = \boldsymbol{FQ}, \quad \boldsymbol{B} = (\boldsymbol{GP})^T \tag{8}$$

where $\boldsymbol{P}$ and $\boldsymbol{Q}$ are matrices which are constrained to satisfy $\boldsymbol{QP}^T = \Sigma_3$, where Σ_3 is a 3×3 diagonal matrix constructed by the first three rows and columns of Σ. Σ_3 is thus a diagonal matrix that contains the biggest three singular values of $\boldsymbol{W}$. We then get a least squared approximation $\boldsymbol{W}^*$ of $\boldsymbol{W}$ as

$$\boldsymbol{W}^* = \boldsymbol{F}\Sigma_3\boldsymbol{G}^T . \tag{9}$$

Thus, the Frobenius norm of the difference between $\boldsymbol{W}^*$ and $\boldsymbol{W}$ is

$$\left\|\boldsymbol{W} - \boldsymbol{W}^*\right\|_F = \sqrt{\lambda_{k+1}^2 + \ldots + \lambda_n^2} .$$

We define the cost of this approximation as

$$Cost = \frac{\left\|\boldsymbol{W} - \boldsymbol{W}^*\right\|_F}{\left\|\boldsymbol{W}\right\|_F} = \frac{\sqrt{\lambda_{k+1}^2 + \ldots + \lambda_n^2}}{\sqrt{\lambda_1^2 + \ldots + \lambda_n^2}},$$

which is the Frobenius norm ratio of approximation difference $\boldsymbol{W}$-$\boldsymbol{W}^*$ and the original data set $\boldsymbol{W}$.

Lower rank approximation has an advantage of avoiding noise. Recall that noise is one of the reasons that we can not get the exactly three singular values from SVD decomposition of image matrix W, which means that the noise prevents the singular values from dropping off and makes them bigger. This gives us some hint that maybe we can get rid of the noise by setting those singular values to be zero.

Note that there is ambiguity existed in Eq.(7) because any $\boldsymbol{P}$ and $\boldsymbol{Q}$ satisfying constrain $\boldsymbol{QP}^T = \Sigma_3$ and equations $\boldsymbol{P} = \boldsymbol{AP}$, $\boldsymbol{Q} = (\boldsymbol{A}^{-1})^T\boldsymbol{Q}$ will satisfy equations in (8), where $\boldsymbol{A}$ is an arbitrary invertible matrix. This means that we can only get the solution of $\boldsymbol{B}$ and $\boldsymbol{\Phi}$ up to a linear transformation. Reference [4] proves that knowing $\boldsymbol{A}$ is unnecessary for synthesis new image if the object is viewed from front-on. In other cases, additional information should be used to determine the linear transformation.

From the illumination model (1), Eqs.(2) and (7), we can predict the appearance of an object with respect to any direction of light source $\boldsymbol{s}$ if the pose of object is fixed and the base matrix $\boldsymbol{B}$ is calculated. Estimation of $\boldsymbol{B}$ up to a linear transformation needs to use the relationship in Eq.(8). To determine the linear transformation $\boldsymbol{A}$ fully or partially, we developed several ways. The first way is to use the knowledge of given light source directions. The second way takes advantage of priory knowledge about the class of the object, and the third way is directly selection of bases. A nice feature of our methods is simple and efficient, new image can be synthesized in linear time (that is $O(n)$).

4.1 Estimation of *B*

When the light directions of sample images are known, matrices $\boldsymbol{P}$ and $\boldsymbol{Q}$ can be uniquely determined according to Eq.(8) and constrain $\boldsymbol{QP}^T = \Sigma_3$. Recall that we have an important observation in Section 2, which is that if we constrain lighting direction $\boldsymbol{s}$ is equal to coefficient vector $\boldsymbol{\Phi}$, then base matrix $\boldsymbol{B}$ constitutes of three images lit from three coordinate directions. Thus, we have

$$\boldsymbol{Q}=\boldsymbol{F}^{+}\boldsymbol{s}\;;\quad \boldsymbol{P}=(\boldsymbol{Q}^{-1}\Sigma_3)^T\;.$$

$\boldsymbol{B}$ can then be calculated by least squared criterion

$$\boldsymbol{B}=(\boldsymbol{GP})^T=\boldsymbol{Q}^{-1}\Sigma_3\boldsymbol{G}^T\;. \tag{10}$$

Thus, given any new light directions, novel images can be rendered. This method can be used provided that light can be well controlled during image capturing.

It is unrealistic to assume that the light source directions of sample images are given. We need a method that can estimate the light properties and the surface properties simultaneously. One way that deals with unknown light direction is to suppose that we know the domain knowledge of the class of objects. If we know the base function $\boldsymbol{B}$ of a prototype member of the class, for example, assume that we know B_f for a prototype object f. Then, when we get image data of a new object, we will estimate its $\boldsymbol{P}$ and $\boldsymbol{Q}$ matrices by assuming that it has the same surface properties as the prototype. Thus we estimate $\boldsymbol{P}$ by minimizing

$$\left|\boldsymbol{B}_f-\boldsymbol{GP}\right|^2, \tag{11}$$

where $\boldsymbol{G}$ are computed from the new dataset. The solution $\boldsymbol{P}^*$ of Eq.(11) are then used to solve the surface properties by using

$$\boldsymbol{B}=\boldsymbol{GP}^*. \tag{12}$$

Thus, $\boldsymbol{Q}$ and the direction $\boldsymbol{\Phi}$ can be determined uniquely. Example is shown in Fig.6. The input image data are generated from Visible Human data and three base images are estimated by using the base images of ball data (see next section). Figure 7 shows images generated by derived base matrix $\boldsymbol{B}$.

Alternatively, it is not difficult for us to select three images lit from independent directions as the base images. For example, images lit from front, side and above (see Fig.9). Then, given any one of the other images, coefficient vector can be estimated via Eq.(4). Moreover, if the base images are lit right from coordinate axes directions, then it is easy to derive the relation between lighting directions and images because the coefficient vectors are the lighting properties in this case. Otherwise, we should know illuminants of the base images. If light directions of the three base images are known, then the coefficient vector and new image corresponding to any specified light direction can be computed. Figure 9 is an example of images synthesized from three selected base images.

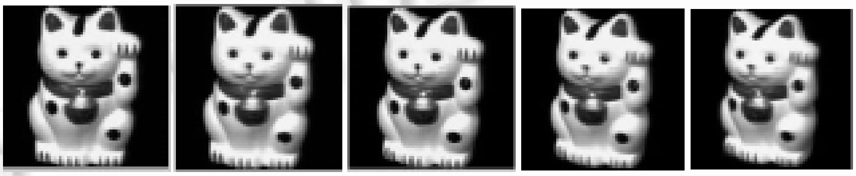
4.2 Morphing and animation

Fig.1 Light morphing

Through SVD, image matrix can be decomposed and its principal singular value and base images (or principal components) are extracted (Eq.6). If needed, image matrix can be approximated in a low rank space to get rid of noise and obtain a compact representation of dataset (Eq.8). Generally, specifying a set of coefficients with respect to the base images will reconstruct one of the input image or synthesis a novel image.

In this subsection, we discuss how to generate a morphing sequence via SVD. To this end, we need only a few images of the object as input. After SVD decomposition of image matrix, we have $\boldsymbol{W}=\boldsymbol{U}\Sigma\boldsymbol{V}^T$. Denote $\boldsymbol{B}=\Sigma\boldsymbol{V}^T$ as the base matrix that characterizes the principal components and directions of input images, and denote ***U*** as coefficient matrix. Thus, any input image can be represented by linear combination the base matrix with a vector of corresponding coefficients. By linear interpolating coefficients we can generate a morphing series of the object varying along the geometrical or photometrical properties. Results of linear interpolation are satisfied and reasonable because we have assumed that objects close to be diffuse and convex. Moreover, self-shadow and specularities can be approximated by linear interpolation if the number of base images is more than three. In our experiments, if the principal components represent light changes, then interpolation of the coefficients will generate movies of the smooth variation of the illumination impacting on the object. We call it *light morphing* (see examples in Fig.1, which use three input images lit from left, front, and right, respectively.). If the principal features characterize the pose changes of the object, then we generate a *view morphing* series of the object (see examples in Figs.(2) and (3). In fact, Fig.3 illustrates appearance changes in both geometry and photometry. Note that the highlight on the bell is also moved correctly.

Fig.2 Input images represent object rotation



Frame2 Frame6 Frame12 Frame16 Frame20

Fig.3 Some frames extracted from the morphing series

Morphing generated by SVD is more compact and efficient than feature-based and mesh-based method because images are expressed by the base images and a set of coefficients, which is much less than the number of feature lines and control points of mesh. Note that advanced algorithms should be developed if accurate self-shadows and specularities are required.

5 Experiments

The first experiments use a set of computer generated ball images for which the surface material and light source directions are well controlled to satisfy our assumption. The image set is generated by changing of the elevation and azimuth of light source direction. The view coordinate is set such that *XY* plane aligns with the screen plane, *Y*-axis points to the top of the screen, *X*-axis points to the right of the screen and *Z*-axis is perpendicular to and point out of the plane. The dataset covers a half sphere space of light directions where *z* larges than zero. After SVD decomposition, the rank of the image matrix is 72, and singular values are plotted in Fig.4 where you can find the singular value deduced very quickly.

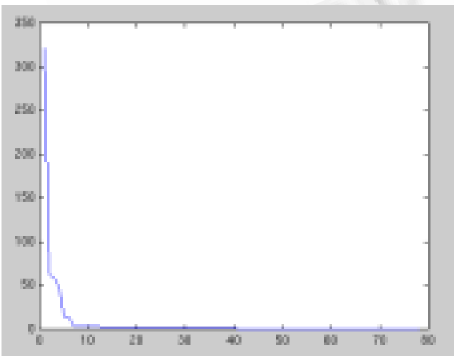


Fig.4 All singular values of the ball dataset

We take the biggest three singular values to create a low rank approximation of the dataset and generate three base images shown in Fig.5. The Cost of this rank 3 approximation is 0.0059. These images show that the light directions of the three base images consist with three coordinate axes. Novel images under any specified light directions using three base images estimated from SVD.

The second experiment assumes that light directions are unknown. Our image data are rendered from Visible Human Dataset and controlled in the same light direction settings as that of the ball data. Notice that shape of the man head is similar to a ball, thus, when estimate the base images, we first compute the SVD decomposition and low rank matrix $\boldsymbol{G}$ of this dataset, then estimate matrix $\boldsymbol{P}^*$ using the base matrix $\boldsymbol{B}$ computed from the ball data (Fig.5). Finally, the base images of human dataset can be calculated by Eq.(12). Figure 7 shows some synthesized images by linear combination of three base images.

Figure 8 is another experiment that uses the face database from Harvard University. We select three images from the dataset that was lit roughly from the directions of three coordinate axes. This selection makes the base matrix of illumination sphere close to identity matrix. In other words, the light directions can be simply regarded as the coefficients of combination. Novel images lit from other lighting directions can be thus generated by linear combination of the base images.

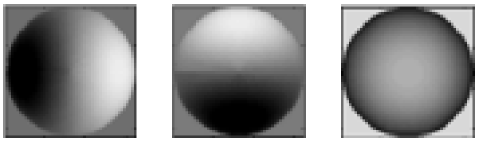


Fig.5 Three base images of a ball dataset

(a) The three base images calculated from known class object (b) The three base images calculated from known light directions

Fig.6

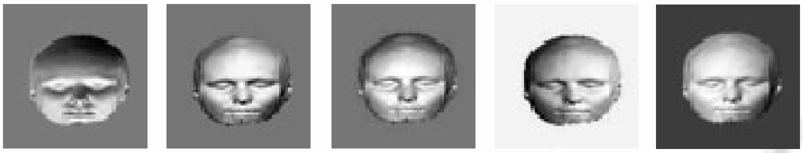


Fig.7 Synthesized head images

Fig.8 Base images extracted from Harvard face database

Fig.9 Face images synthesized from above base images

6 Conclusion

In this paper we introduce an image-based approach that use singular value decomposition to synthesis novel images of an object under any lighting directions, rather than recovering BRDF function or any other reflection parameters. This method is shown to be very efficient and can generate continuous object morphing sequence under varying of illuminations and object pose.

Limitation of this method is that albedo and shading information are combined indiscriminatingly. However, because human eyes are less sensitive to the accuracy of lighting changes than to that of geometry changes, the proposed method can satisfy most image based applications.

Acknowledgement Data used in this paper are from Harvard and Yale face database, Columbia object database and the Visible Human Dataset.

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变化光照的对象图像合成

徐 丹[1], 王平安[2]

[1](云南大学 计算机科学与工程系,云南 昆明 650091);

[2](香港中文大学 计算机科学与工程系,香港)

摘要: 光照是真实感图形绘制和许多图像应用中的一个非常重要的因素.提出了一种完全基于图像的方法来反映光照变化在绘制对图像时的影响.所提出的方法不是直接去估计对象反射模型中的参数，或是去拟合 BRDF 函数,而是用奇异值分解(SVD)来拟合 Lambertian 对象在光照和几何朝向变化情况下的所有图像集合.其中,光线方向的解析表达可以由样本图像、基图像以及已知类对象的图像集导出,对象在新的光线方向下的图像可通过适当地线性组合基图像而有效地绘出.另外,利用对 SVD 系数的线性插值可以生成反映对象几何朝向和光线变化的连续变形图像序列.特点是为表示给定对象的图像集以及合成新的图像提供了一种简单且紧缩的方法,较适合于基于图像的应用.

关键词: Lambertian 模型;奇异值分解;光照;基于图像的绘制;图像变形

中图法分类号: TP391 文献标识码: A