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Master's Thesis

Fast User-Weighted Viewpoint/Lighting Control for Multi-Object Scene

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(심사청구서)

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Contents

List of Tables

List of Figures

Abstract

Fast User-Weighted Viewpoint/Lighting Control for Multi-Object Scene

In computer graphics, automatic viewpoint selection for model has been performed by evaluating the goodness of sampled viewpoints and selecting the best one. Various approaches have been attempted to define a good viewpoint, and entropy and mesh saliency have been used for the purpose of the user. In this paper, we propose a method for selecting the best viewpoint and lighting for a multi-object scene, based on the user importance of each object. After sampling the lighting surrounding the scene and the viewpoint inside, the result image is rendered by combining the sampled viewpoint and lighting. We then select a result most suitable for the user importance of each model. While this technique obtains the most suitable viewpoint and lighting for the user's needs, it has disadvantage of high cost due to the need to render all combinations of sampled viewpoints and lightings. In order to minimize the computation cost, a pixel classification method which parallelizes image analysis on GPU and coarse-to-fine sampling method is also proposed in this paper. The proposed method is able to estimate the viewpoint and lighting of multi-object scene fast, and proved the effectiveness of the method using a benchmark based on the user data.

Keywords: viewpoint selection, lighting selection, visual attention, metadata

Ⅰ. Introduction

In computer graphics, most of the graphics technology is based on the 3D model. In order to optimize the rendering of the scenes containing these models, it is very important to locate the viewpoint and lighting. In addition to optimizing the target rendering technology, the images generated using the selected viewpoint and lighting information can be used in areas such as image based rendering [1, 21], which uses images instead of 3D geometry model, and computer vision. However, these tasks are usually done by hand, and the user had to spend a lot of time to select the desired combination of viewpoint and lighting. There have been studies to select good viewpoint and lighting automatically [8, 20], and a method of selecting the viewpoint/lighting that best suits the quantitative definition of a good viewpoint/lighting. However, in the conventional method, only one property (viewpoint or lighting) is estimated while the other property is fixed. Since the viewpoint and lighting are properties that affect each other, the viewpoint/lighting combination that estimated sequentially is not optimal. Therefore, in order to select a scene-optimized combination, it is necessary to use a pair of viewpoint and lighting as a unit. It is difficult because the number of combinations is increased to a square as compared with estimating only one of them.

In the past research, we proposed a method to find optimal viewpoint and lighting based on the user importance for each model of multi-object scene [2]. In this method, a sample for selecting a viewpoint and lighting is generated, and then images are rendered through combinations of sample viewpoints and lightings. The ratio of the properties of the rendered image to the model is compared with the ration of the importance set by the user. The result with the smallest difference is the most appropriate combination for the user importance. This method has an advantage that it can obtain a viewpoint applying the importance of each model in the multi-object scene, and also generate a position of lighting that greatly affect the rendering result. In order to improve the performance, we proposed a pixel classification method for each model using GPU which minimizes the calculation cost of each object.

In this paper, we propose a method to approve the previous research which to select the viewpoint and lighting fast. The method generates only a small number of sample viewpoints and lightings. The optimal combination is firstly selected by the previous method with combinations of samples. A new optimal combination is selected by the same method with combinations of new samples generated around the optimal combination of viewpoint and lighting by previous step. By repeating the steps and incrementally increasing the sample density, the computational cost for a sample of the same density can be logistically reduced.

The contribution of this paper is as follows. First, our solution selects the viewpoint and lighting in combination, and it is more appropriate than selecting them privately. Second, our method targets scenes containing multiple objects, and provides an optimal combination of user importance for each object. Third, indicators for evaluating the combination are designed to meet the needs of users by taking into consideration various properties at the same time that affect human perception. Last, GPU pixel classification and coarse-to-fine sampling methods enable fast selection. We will introduce more detail as follows.

Ⅱ. Related works

In computer graphics and vision, several studies have been conducted on techniques for automatically setting viewpoints and lighting for scenes. The key problem of selecting a viewpoint is that which viewpoint is a good point, and ways to quantify the quality of the viewpoint have been proposed to answer this question [4]. The best viewpoint can be the point of showing the part that makes up the model as much as possible or showing the part where the importance of the model is the highest. Blanz et al. [5] explained that the conditions of a good viewpoint can be determined by various factors, including the ease of recognition, familiarity, functionality, and esthetic standards. Kamada et al. [6] used the normal vector of all faces of the model and the angle between the direction of viewpoint to search the best viewpoint. This method has the problem that it is possible to select the viewpoint that the faces of the model are as much as possible in the field of view, but the result may not actually contain necessary information.

Various studies using entropy [7] have also been conducted to reflect the information that contained in the model into viewpoint selection [8, 9, 10]. The information of the model provided by the sample viewpoint is expressed in the form of entropy, and then selects the best viewpoint. A study has been conducted to express context information of the model [11]. The view likehood based on the probability of observing the model and the view stability, the change of the model as the viewpoint changes, are used as a representative indicators [12]. However, this method has a disadvantage that it does now include a human perception. Mesh saliency [13, 14, 15, 16, 17] is commonly used to study approaches considering human perception. This method uses the visual attention of the surface of the model to select the point that causes the most human interest. Recently, an approach is being tried to learn a good viewpoint by using AI [18, 19].

Lighting selection is also done in a similar way to the viewpoint. In Gumhold's study [20], the entropy according to the location of the light source was calculated and the lighting containing the most information was selected.

Dutagaci et al. [22] purposed a benchmark, view selection error (VSE), to quantitatively evaluate the performance of the viewpoint selection algorithm. VSE is the degree of error by using the ground truth, the good viewpoint selected by users. First, create sample points at a constant density on the sphere surface surrounding the model, and group viewpoints that generate similar result images (symmetry set). Approximates the user's ground truth set to the nearest sample viewpoints set, and includes the symmetry set of the approximated sample set. The normalized difference of the result viewpoint of target algorithm and nearest one in sample set is VSE. In the study, 26 people participated in 68 models to produce ground truth. The smaller VSE value means better performance.

Ⅲ. Algorithms

1. Sample Rendering

In this section, we describe how to generate samples of viewpoint and lighting, and render image by sampled combination.

A. Virtual viewpoint sampling

The virtual viewpoint is sampled so that the model can be observed in various directions. Since it is inappropriate to look up the model from bottom to top, we use only the viewpoints of the center of the model from the hemisphere area surrounding the model. The viewpoint samples on the hemisphere region can be represented by using two variables θ and ϕ as shown in Fig.1. Variable θ is the latitude, that represents the degree to which the sample is tilted from the xy plane of model. Variable ϕ is the longitude and represents the degree to which the sample projection onto the xy plane rotates from the x axis. Both variables are uniformly sampled to create a viewpoint samples on hemisphere.

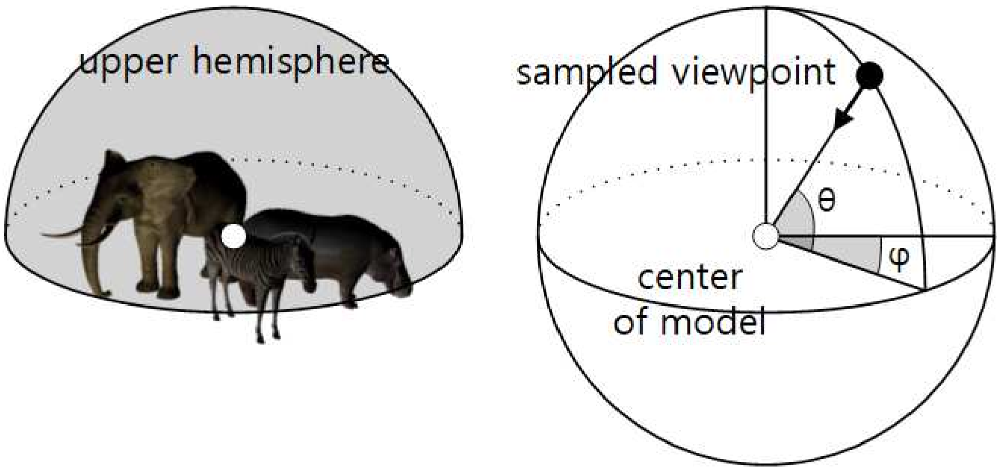

Figure 1. Virtual viewpoint sampling

B. Virtual lighting sampling

Sampling a virtual light source that illuminates to the scene. The light source affects the brightness and contrast used as indicator of the viewpoint/lighting selection by giving the difference in brightness to the model. In real world, light have many various types depending on properties (wavelength, shape of light source, spreading), but in this paper, virtual lighting is sampled only a point light source.

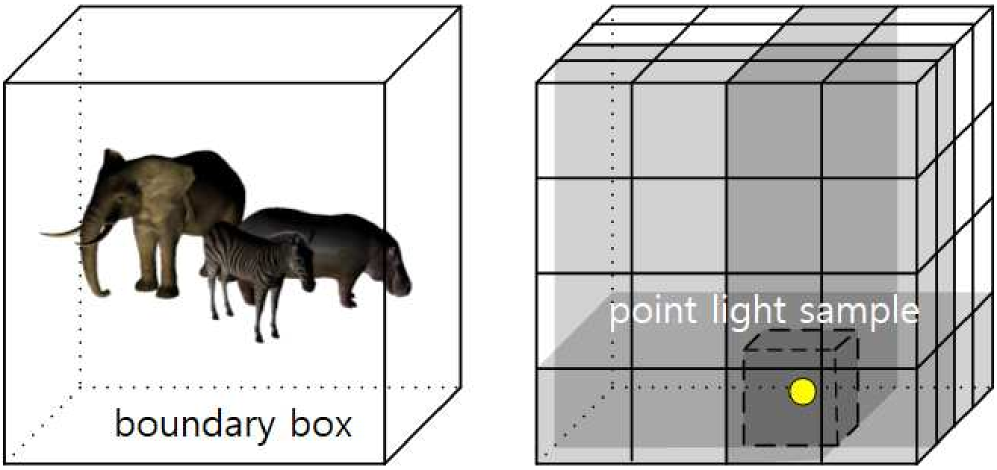

Figure 2. Virtual point light sampling

Point light source is a light source in which light is emitted in all directions from a light source. Since the direction of incident light changes according to the position of the point light source, it is preferable to sample the light source at various positions in space. Since the point light source is far away from the models, it produces a similar effect as the directional light source, so we create a bounding box that encloses the model as shown in Fig.2. Divide the bounding box into cells of a certain size, create a light source in the center of cell. The position of the sample point light source can be represented by the boundary box and the index information of the cell.

C. Image rendering with the samples

The image is rendered using a combination of the sampled point and lighting. The Phong reflection model is used for rendering, and the generated image pool is used in the process of viewpoint/lighting selection suited to the user importance mostly in the following process.

2. Sample Evaluation

Select the viewpoint/lighting combination that best fits the object importance set by the user. In this paper, properties used to quantify the object's visual attention are brightness (luma), area, and contrast. The difference between the respective ratio of properties and user importance is calculated, and the viewpoint/lighting model having the smallest value is selected. The kind of the property can be freely changed according to the demand of the user.

As the area occupied by the object on the image becomes wider, the visual attention of the object becomes higher. There is a way to use the bounding box or silhouette of the object when the area of the object is required. However, in this study, we use the actual area. Since the area is proportional to the number of pixels occupied by the object on the screen, this value can be used as the area of the object.

The object brighter than the other objects has higher visual attention. Indicators of brightness include luminance and luma. The luminance refers to the luminous intensity per unit area, and the luminance of one pixel is proportional to the luminous intensity because all the pixels have the same area. Therefore, the luminance of the pixel set is equal to the average of the luminance of all the pixels in the set. Luma is a concept similar to luminance, but luminance means physical brightness, while luma means the perceptional brightness by a person. Therefore, in this study, luma was used as an indicator of brightness with an emphasis on user's visual attention. Luma Y' is expressed as the following equation using the RGB channel value of the pixel.

$$Y' = 0.299R + 0.587G + 0.114B$$

Contrast represents the difference in brightness or color that makes objects appear to be distinct from each other. Therefore, the objects which shows larger contrast are more noticeable and higher visual attention. Weber [3] contrast is not appropriate for calculating the contrast within an object, because it uses the difference between the brightness of the background and the object. Michelson contrast [3] only use the maximum and minimum brightness values of the pixels, it cannot express feature of whole image. We then adopt the root mean square (RMS) contrast which can consider the influence of all the pixels in the object, and the RMS contrast c for the set of n pixels (p) is as follows:

$$c = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y'_{p_i} - \overline{Y'})^2}$$

It is necessary to judge whether or not the visual attention metrics obtained for each object are appropriate for the user importance. To solve this problem, we define the ratio error, which represents the difference of the ratio between the indicator and user importance of the object. The ratio error (e) of the object (o) with respect to n indicators, m objects, and corresponding importance (w) is given by the following equation.

$$e = \sum_{o=1}^{m} \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{w_o}{\overline{w}} - \frac{x_{oi}}{\overline{x_i}} \right)^2}$$

The larger ratio error means the greater difference of ratio of the indicators from the ratio of the user importance. So the viewpoint/lighting model with the smallest ratio error is selected.

3. Pixel Classification

The area, brightness, and contrast can be calculated by reading all pixels of image and classifying them by object sequentially on CPU. However, this method has a disadvantage in that it is very expensive to apply all the sample images. In this section, we describe how to classify information of pixels on parallel.

The problem can be mitigated by using GPU to process all pixels in parallel. As shown in Fig.3, information of the position of each pixel is transmitted to the vertex shader using a vertex array containing coordinate information of all pixels. Next, the rendered image using sample viewpoint and lighting is transferred to the texture, so that the pixel information stored in the texture can be read by the position. A hash function is applied to the object ID stored in the texture to classify the pixels having the same ID, and they can be collected in one fragment. The fragment shader accumulates classified pixels in one fragment for each object through blending.

In case of the area, the number of pixels including to the object can be obtained by accumulating one to fragments, which is the number of pixels per pixel. The brightness of the object is obtained by cumulative value of brightness and total number of pixels (area). The contrast is obtained by the difference from average brightness and brightness of each pixel in the same process.

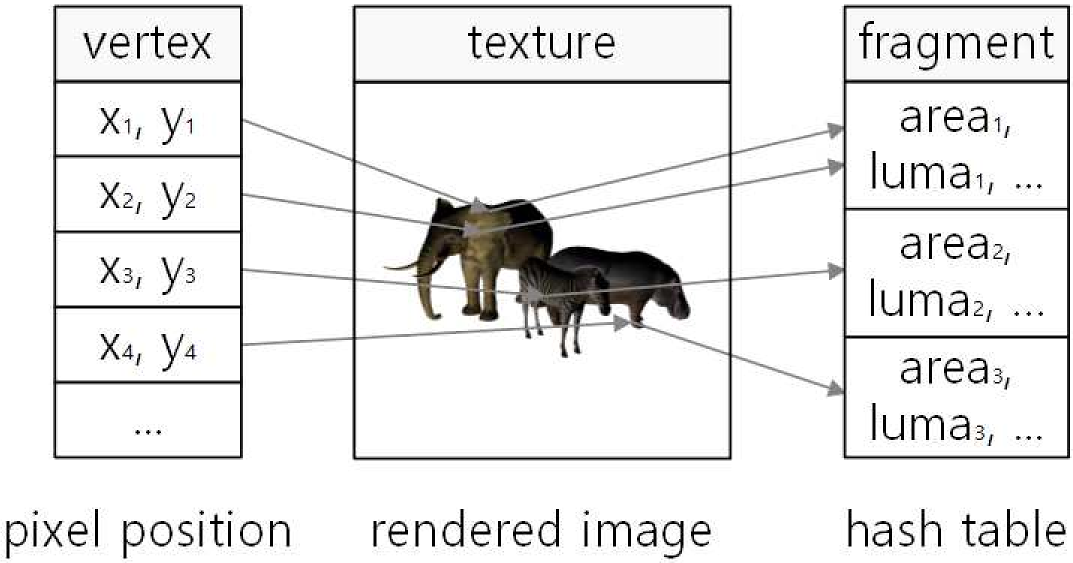

Figure 3. Overview of GPU pixel classification

4. Coarse-to-fine Sampling

Although GPU-based pixel classification techniques reduce the computational cost of a single viewpoint and lighting combination, the main bottleneck factor in the proposed algorithm is the delay caused by rendering all the combinations of viewpoints and lightings. The time complexity of our algorithm using n viewpoints and m lightings samples is $O(nm)$, which is a high cost operation that goes over the minutes even when parallel pixel classification is applied. Therefor, we propose a coarse-to-fine (CTF) sampling method that does not rendering and evaluation for all combinations, but sequentially finds the appropriate combination by increasing the density of the sampling.

Fig. 4 is a schematic diagram of the proposed CTF sampling method. In the first step, we do not generate all of the desire density of samples, but we create low density samples (yellow points) and apply our algorithms to select the best combination (red point). Create a new low density sample around the selected combination in the next step. These processes are repeated and end when the sample density is reached at target density. In the k steps to reach target density, the time complexity of the CTF sampling method is $O(k(nm)^{\frac{1}{k}})$ which can be processed fast even if n and m are large.

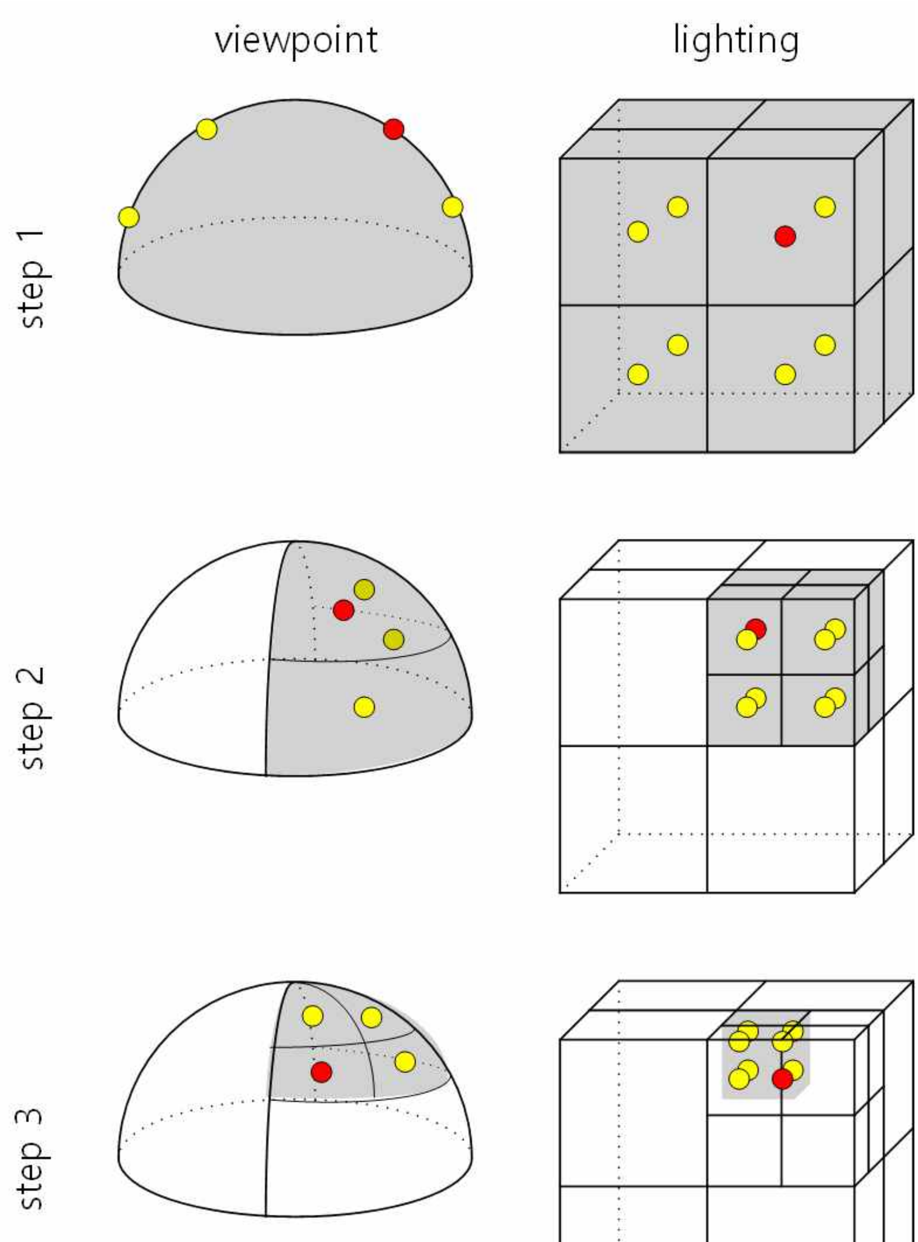

Figure 4. Illustration of coarse-to-fine sampling method step-by-step

Ⅳ. Results

Our proposed method is implemented in Intel Core i7-7800X 3.50GHz, NVIDIA GeForce GTX 1080 Ti. The rendering performance of the whole process of the viewpoint/lighting control method using the GPU pixel classification and coarse-to-fine sampling method is about 128ms for the 256×256 resolution in the model composed of 60203 triangles, and the 8×8 viewpoint and 8×8×8 lighting sample density. The rendering performance are classified according to the resolution and GPU pixel classification method and coarse-to-fine sampling method on Fig. 5. Since the performance of the acceleration method using the GPU is and additional process of generating hash texture, when the resolution is low, it is relatively slow as compared with the processing by CPU, but as the resolution is higher, the performance is better than the CPU. When applying the coarse-to-fine sampling method, the performance is 300 times faster, which will increase as the sample density of the viewpoint and lighting increases.

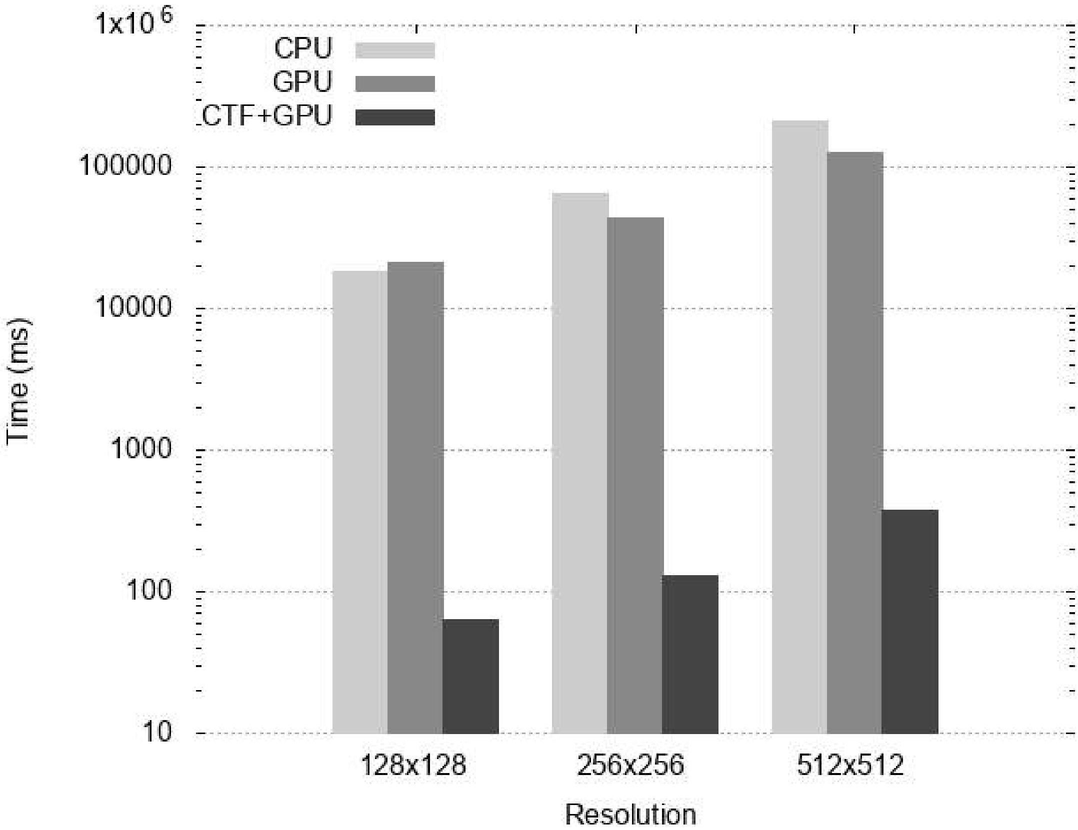

Figure 5. Evolution of performance with respect to resolution

We use the VSE, a benchmark proposed by Dutagati et al, for quantitative evaluation of algorithm performance. VSE is a benchmark that caculates the degree of error by using the good viewpoint for the model selected by the users as the ground truth. The VSE proposed in study is based on 68 3D models and ground truth from 26 subjects. Our study targets a scene that contains multi-object, we generate our the ground truth for multi-object scene in same manner as VSE. First, users select good viewpoint on target multi-object scene with importance for each object and generate ground truth. And generates a set of sample viewpoints of the sphere showing the rendering result similar to the rendered image at the collected viewpoints. The normalized distance between the viewpoint selected by the algorithm and the nearest point in the set is VSE value. VSE is a benchmark defined only for viewpoints, but it has also been applied to lighting. In this study, ground truth of 7 subjects and 12 scenes were measured. Table 1 campares the average VSE of the proposed algorithm with the average VSE measured by LAGA et al. [23] and the seven representative viewpoint selection algorithms presented in the VSE paper. When the coarse-to-fine sampling method is applied, the VSE value is increased because it does not check all the combinations of viewpoint and lighting samples.

Viewpoint Selection Algorithm	VSE
View area	0.517
Ratio of visible area	0.473
Surface area entropy	0.396
Silhouette length	0.446
Silhouette entropy	0.484
Curvature entropy	0.474
Mesh saliency	0.430
Data-driven	0.353
Proposed algorithm (without CTF sampling)	0.325/0.410
Proposed algorithm (with CTF sampling)	0.458/0.501

Table 1. Average VSE of the viewpoint selection algorithms

In addition to using the three features of area, brightness and contrast used in this paper, we compared the time and quality when using only the view area and CTF sampling. Since only one feature was used, the ratio error can be used as an indicator of quality. The comparison was performed on a scene with three objects for a resolution of 512×512, and the number of viewpoint/lighting samples used are shown in Table 2. As result, the algorithm using CTF sampling showed a ratio error close to high-density sampling, and showed better quality at a similar speed to low-density sampling.

Viewpoint Selection Algorithm	Time	Ratio Error
View area ($8^3 \times 8^2$ samples)	23525ms	0.245
View area ($2^3 \times 4 \times 3$ samples)	71ms	0.302
View area + CTF ($2^3 \times 2^2$ samples, 3 levels)	73ms	0.266

Table 2. Time and average ratio error of the view area based viewpoint selection algorithms

Fig. 6 and 7 shows a result of a rendered image using the selected viewpoint and lighting using the proposed method. We use three scene statues, band and animals. In the result images of statues scene the model with the highest user importance was located at the center of the image. This is because the area occupied by model on the screen can be widened, when the target model is placed in a region close to the viewpoint. The pegaso model in the 6-(b) is brighter than the other two models because it is affected by the brightness among the properties. In addition, the model with the highest user importance shows the obvious shading effect compared with the other models in the overall result.

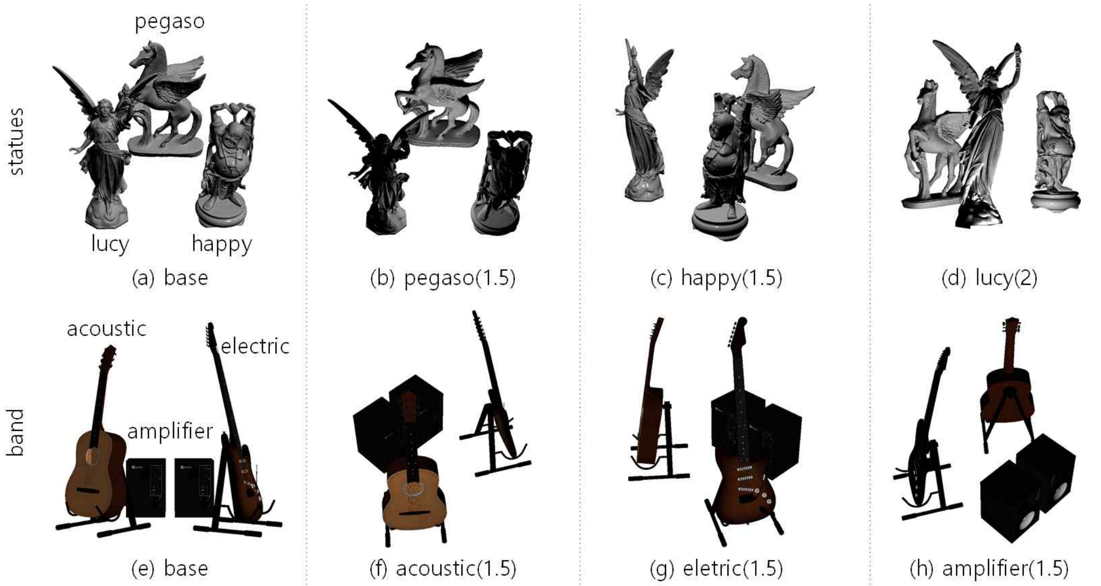

Figure 6. Result of viewpoint/lighting selection to input models (statues, band)

In the case of band scene, three models of acoustic, electric, and amplifier were used. In each result image, the model with the highest user importance was positioned at the front of the field of view. In the case of 6-(h), since the base color of the amplifier is dark, the lighting effect is hardly applied to the other two models.

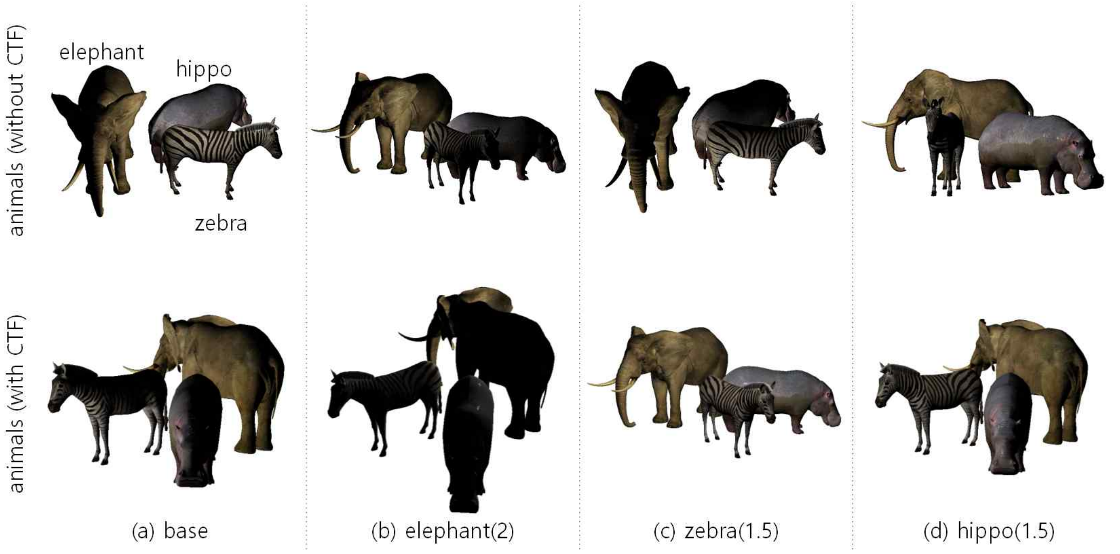

Figure 7. Result of proposed algorithm to animals model with CTF sampling

Fig. 7 shows the result of the animal scene according to whether the coarse-to-fine sampling method is applied. As with the other scenes, the most important model tends to appear at the center of the screen, or to receive intense lighting effects. However, in the case of 7-(b), when the coarse-to-fine sampling is applied, all of the three models are darkened. It is due to the wrong selection of the initial sampling direction, and the method could not modify this error during following the steps.

V. Conclusion

In this paper, we propose a method to automatically select the viewpoint and lighting for a multi-object scene based on user importance. And the method has the advantage that the user can freely adjust the user importance to obtain a desired image. In addition, our method is almost real-time, so interactive operation and modification are possible. In this study, we used the area, brightness, and contrast in the process of evaluating the visual attention of the objects, but user can supplement their desired properties to our viewpoint/ lighting selection frameworks.

Grid-based lighting sampling has the limitation that when a light source is sampled inside an object, it produces an incorrect result image. A model with a light source inside is dark, while the other model illuminated. This problem can be solved by adding a condition to sample only outside of the object during the sampling of the light source, but adding such a process at each step of the CTF sampling will be a costly performance burden. Fortunately, when calculating the ratio error using user importance, if the feature of brightness is used, most of cases of object-inside light sources can be removal.

However the proposed method has a disadvantage in that it is difficult to find the optimal viewpoint and lighting when the sample in the wrong direction is initially selected. So, in the future, we research method using more detailed sampling initially to find more precise directions, or a user data based method of selecting an initial approach direction by receiving additional user input.

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논문요약

다객체 모델에 대한 사용자 중요도 기반 고속 시점/조명 조절 기법

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소프트웨어플랫폼학과
김 태 문

컴퓨터 그래픽스에서 시점의 자동 선택은 일반적으로 시점을 샘플링하고 샘플링한 시점들을 평가하여 가장 우수한 시점을 선택하는 방식으로 이루어졌다. 좋은 시점을 정의하기 위한 다양한 접근이 시도되었으며, 사용자의 목적에 따라 엔트로피, 메쉬 주목도 등이 사용되었다. 본 논문에서는 다수의 모델로 이루어진 장면에 대해 사용자의 모델별 중요도에 기반하여 시점과 조명을 선택하는 기법을 제안한다. 장면을 둘러싸는 시점과 내부에 분포된 조명을 샘플링한 후, 샘플 시점과 조명을 조합하여 결과 이미지를 렌더링한다. 렌더링 이미지의 모델별 주목도를 이용하여 사용자가 설정한 중요도에 가장 적합한 결과를 선택한다. 이러한 기법은 사용자의 요구에 맞는 시점과 조명의 조합을 얻을 수 있지만, 조합 전부에 대한 렌더링으로 인해 연산 비용이 크다는 단점이 있다. 그러므로 본 논문에서는 연산 비용을 최소화하기 위해 GPU를 통해 이미지 분석을 병렬화한 객체별 픽셀 분류 기법과 저밀도의 샘플을 생성하여 가장 적합한 조합을 선택하고, 그 주변에 다시 샘플을 생성하여 점진적으로 샘플링을 진행하는 기법을 추가적으로 제안한다. 제안한 기법을 통해 신속하게 다객체 모델에 대한 시점과 조명을 추정하는 것이 가능하며, 사용자 실측

기반의 벤치마크를 이용하여 기법의 유효성을 입증하였다.

주제어: 시점 선택, 조명 선택, 시각적 주목도, 메타데이터

(표지측면)

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