Time-Sequence Dynamic Virtual Images*

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Abstract

In this paper, we propose to reconstruct time-sequence dynamic virtual images. At different time of a day or different weather conditions the same scene is differently lighted. Using General Regression Neural Networks the rule of lighting conditions changing with outside conditions can be infered, thus the virtual images in virtual outside conditions can be obtained from a real image of the scene. So using the method presented here we can reconstruct virtual images at any apppointed virtual time or weather condition. Any geometrical information of the scene is not needed in generating virtual images. Combining IBMR techniques or panoramic image techniques, the model of scene is recovered. Further, combining the dynamic virtual images obtained by our method, time-sequence dynamic virtual scene can be reconstructed and revisited in virtual reality.

Keywords: *Image-Based Modeling and Rendering (IBMR), Dynamic Reconstruction, General Regression Neural Networks (GRNNs), Virtual Reality*

1. Introduction

One of the important aims of the computer graphics researches is realistic image generation. Image-Based Modeling and Rendering(IBMR) techniques are powerful alternatives to traditional geometry-based techniques for image synthesis. Image-Based Rendering(IBR) techniques render novel viewpoint images from input images. Acquiring geometric models of scene has been the subject of research in interactive Image-Based Modeling techniques, and is now becoming practical to perform with techniques such as interactive photogrammetry. Acquiring the corresponding appearance information (under given lighting conditions) is easily performed with a digital camera.

Image-based rendering can have many interesting applications. Two scenarios, large environments and dynamic environments, in particular, are worth pursuing[1,2]. Until now, most of image-based rendering systems have been focused on static environments. With the development of panoramic video systems, it is conceivable that image-based rendering can be applied to dynamic environments as well.

P.E.Debevec[3] in 1996 put forward projecting real images from dawn to dusk in sun, clouds and even fog weather condition to recovered model, the scene of different lighting conditions is recured. In his method scene images are real images and are obtained in advance, the geometry model of the scene is computed using IBM techniques.

In this paper, we propose to reconstruct virtual images at apppointed time. At different time of a day or different

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weather conditions the same scene is differently lighted. We can infer the virtual images in virtual outside conditions by finding the rule of lighting conditions changing with outside conditions. Using IBM techniques, the model of scene is recovered. Further, combining the dynamic virtual images obtained by our method, time-sequence dynamic virtual scene can be reconstructed. It can be applied in virtual reality to recur virtual scene.

2. Analysis of Image Colors Changing with Lighting Conditions

Figure 1 Color maps shot at different time of a day. There are 28 colors in every image. It is obvious that the colors change with the lighting conditions.

At different time of day or different weather conditions such as noon or night, sunshine or fog, the same scene are different distinctly. Eyes can distinguish the fine variations of colors. So we can accurately recognize things. Watching an image we can approximately know the lighting conditions, time, weather and so on when the image is generated. The same object with different lighting conditions will present different colors in our eyes. The change rules can be found by analysis of changes of those colors. Then we can obtain virtual images under different lighting conditions from a real image. In order to study the change rules, we choose 28 colors and shot these colors at different time of day (see Figure 1). The camera is KODAK DC240. Because the photographs were taken under varying lighting conditions, it was impossible to properly record each photograph with the same amount of exposure. Flash lamp was shut down in order to get lighting informations accurately. It is obvious from Figure 1 that the effect of lighting and shades is different from the shooting time. If we could find out the changing rules of colors with lighting conditions we could deduce novel images under virtual outside conditions from a real image. We adopt neural networks to analyze them.

3. General Regression Neural Networks

General Regression Neural Networks(GRNN) is presented by D.L.Specht in 1991[4]. Specht claim that GRNN is effective with only a few samples and even with sparse data in a multidimensional space. GRNN is radial basis function networks as well as probabilistic neural networks. If probability density function, namely, kernel function adopts Gaussian function GRNNs output is expressed below:

$$Y(X)=\frac{\sum_{i=1}^{n} Y^{i} \exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)} \qquad (3.1)$$

where $D_i^2=(X-X_i)^T(X-X_i)$. X_i and Y_i ($i=1,2,3...n$) are respectively inputs and outputs of samples. n is the number of sapmles. $\sigma$is the width of kernel. The kernel width can be viewed as the perceptive size of nerve cells. Small value for σmeans that the output contribution is mainly from the nearby nerve cells and not from farther ones, and approximation is relatively accurate. Large value forσmeans that the output is from both the nearby nerve cells and farther ones, and is smooth but noisy. The kernel width can be constant or variable. The larger the kernel width is the smoother the function approximation will be. To fit data very colsedly, we use a kernel width smaller than the typical distance between input vectors. To fit the data more smoothly, we use a larger kernel width.

GRNN can approximate any arbitray function with linear or non-linear relatonships between input and output variables. GRNN is suitable for real-time complex modeling due to its fast learning feature and so an advantage for dynamic reconstruction.

4. Time-Sequence Dynamic Virtual Images

σ=40 σ=120

Figure 2 Images obtaining from different Kernel Width. Colors of images are abundant when taking large value of σ.

The colors in Figure 1 are as samples of neural networks, the first image in Figure 3 is the input image, the output images show in Figure 2, the two images in Figure 2 are obtained from two different kernel width values. If we choose a small krnel width then perceptive region is small, there are serious color abruptness, bad smoothness and scarce colors in the image. If we choose a large kernel width, there are wide perceptive region, the good color smoothness and abundant colors but serious color distortion. The larger the kernel width is the smoother the images are. When a large kernel width is chosen, the image contains the lighting information and smoothly balances the lighting changing, namely, lighting changing in the scene is showed up in the images with large kernel width. If we use the images to modulate lighting condition of scene, we can obtain the images with different lighting conditions.

So let

$$y = k_1 x + k_2 f(x) \qquad 4.1$$

where y is virtual image we wanted□x is the input image□ f(x) is the image computed using Formula 3.1, with a large σand the input x. k_1 and k_2 are coefficients.

Figure 3 is the experiment result. Note that the first image in Figure 3 is the original image, which is shot with a common auto camera and then scaned. And there are mountains and sky far away, and also mountains nearby

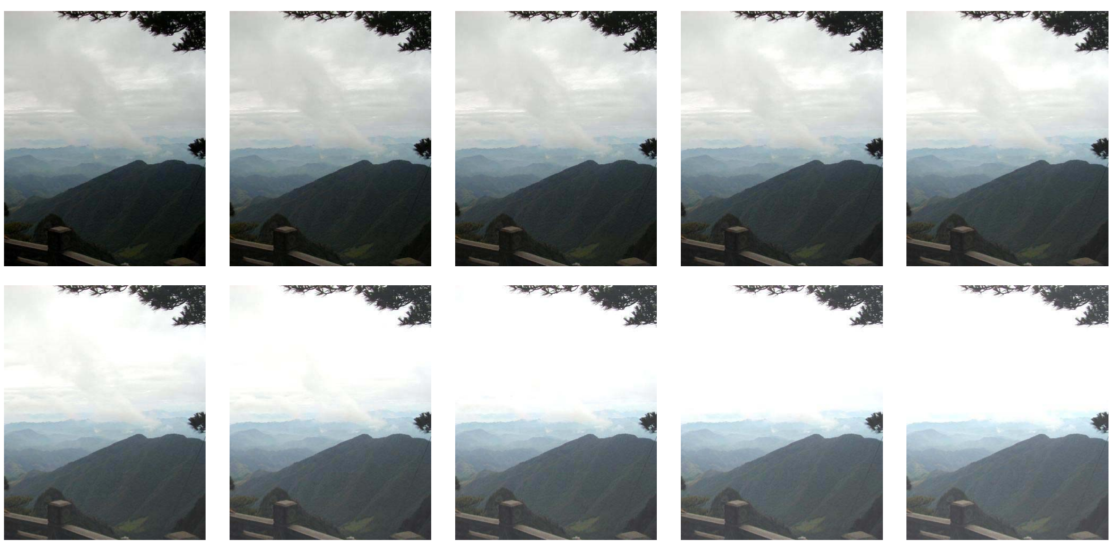

Figure 3 The first image on top row is the original image. The others are virtual images.

and stone fence. Because we did not sample colors when shooting, we have to approximatively utilize samples in Figure 1. The other images in Figure 3 are virtual ones obtained by using the method above. Taking $k_1=1$, we get the different images for different k_2, and the σvalue of the f(x) image is 40 in Figure 2.

If colors of sample are taken at the shotting field at appointed time, the images of the appointed time can be revisited accurately. Using the method presented in the paper, we can deduce virtual images with different lighting conditions from an original image.

5. Application

Method of generating virtual images of the same scene at different lighting conditions is presented, and the inherent relations of color and outside lighting conditions are discovered by the use of general regression neural networks in this paper. As a result, novel images of same scene under different lighting conditions can be deduced from a few known scene images. Using our method, we can obtain the information about the change of lighting in the scene without any space geometry informations.

Panoramic video systems can be applied to dynamic environments. Many systems have been built to construct cylindrical and spherical panoramas[5,6]. Capturing panoramas is even easier if omnidirectional cameras [7] or fisheye lens [8] are used. If the method in this paper is applied to panoramas, time-sequence dynamic environments can be easily revisited. Using IBM techniques, the model of scene is recovered. Further, combining the dynamic virtual images obtained by our method, dynamic virtual scene can be reconstructed.

As in Figure 1, the samples in this paper are 28 colors. As we know, the more the samples there are the more accurate the result will be. However, our samples are less but the images obtained by using our method are realistic.

The questions need to be studied farther: How to choose proper value of σ□k_1□k_2 for the methods presented in formula 4.1 so that the images we obtained are closed to real images. How many sample colors should there be.

6. Conclusions

The methods presented in this paper can generate virtual scene images dynamically and lengthways. We can reconstruct a series of virtual images, which is changed with time. We can also reconstruct images at apppointed virtual time. Only a few images or even one image and some color samples are needed in advance in the method of this paper, any geometrical information of the scene is not needed in generating virtual images, and the computing process is simple. It can be applied in virtual reality to recur virtual scene.

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