CS482: Radiosity

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#### Course URL: http://sglab.kaist.ac.kr/~sungeui/ICG



## Class Objective (Ch. 11)

### Understand radiosity

- Radiosity equation
- Solving the equation



### Questions

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- Multiple questions from a single submission
- Technical questions only related to lecture materials
- I've had some experience working with Monte Carlo Integration as a method for calculating integrals, but how it connects with sampling?
- "(1) About the questions ""Write a question more than 4 times on Sep./Oct."" Does it mean students should at least submit 4 times or after every class we have to submit the questions?
- (2) About the paper, can ACM Transactions on Graphics (TOG) be a paper source?

### History

#### Problems with classic ray tracing

- Not realistic
- View-dependent
- Radiosity (1984)
  - Global illumination in diffuse scenes
- Monte Carlo ray tracing (1986)
  - Global illumination for any environment

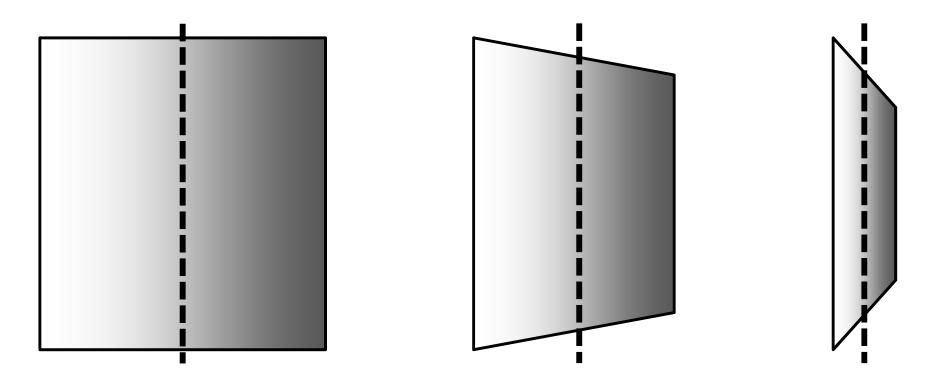


### Radiosity

- Physically based method for diffuse environments
  - Support diffuse interactions, color bleeding, indirect lighting and penumbra
  - Account for very high percentage of total energy transfer
  - Finite element method



### Key Idea #1: Diffuse Only



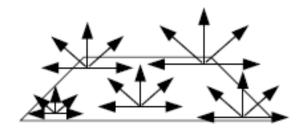
#### Radiance independent of direction

- Surface looks the same from any viewpoint
- No specular reflection



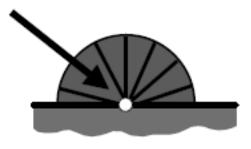
### **Diffuse Surfaces**

- Diffuse emitter
  - $L(x \rightarrow \Theta) = \text{constant over } \Theta$



#### • Diffuse reflector

Constant reflectivity



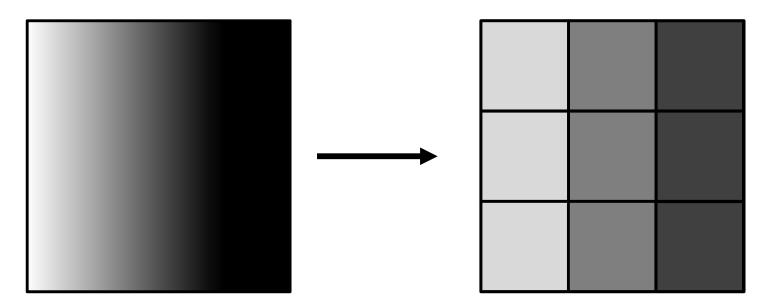
From kavita's slides



## Key Idea #2: Constant Polygons

#### Radiosity is an approximation

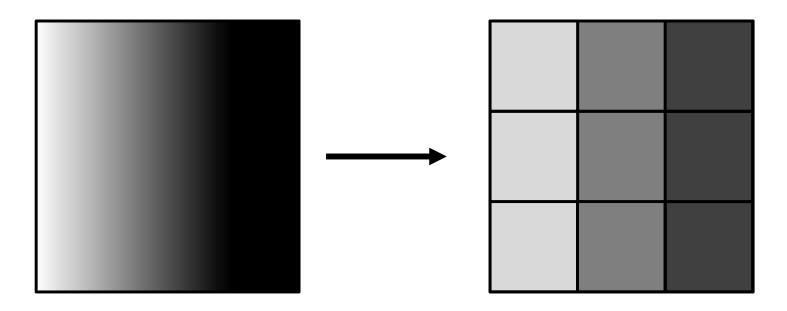
Due to discretization of scene into patches



Subdivide scene into small polygons



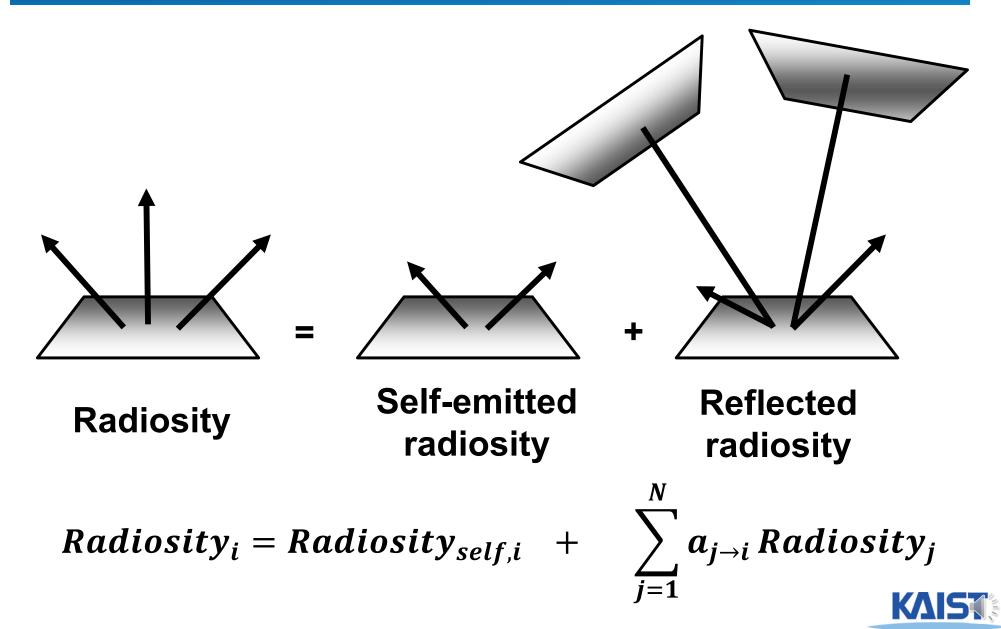
### **Constant Radiance Approximation**



- Radiance is constant over a surface element
  - L(x) = constant over x



### **Radiosity Equation**



## **Radiosity Equations**

#### Radiosity for each polygon i

$$\begin{aligned} Radiosity_{1} &= Radiosity_{self,1} + \sum_{j=1}^{N} a_{j \to 1} Radiosity_{j} \\ &\vdots \\ Radiosity_{i} &= Radiosity_{self,i} + \sum_{j=1}^{N} a_{j \to i} Radiosity_{j} \\ &\vdots \\ Radiosity_{N} &= Radiosity_{self,N} + \sum_{j=1}^{N} a_{j \to N} Radiosity_{j} \end{aligned}$$

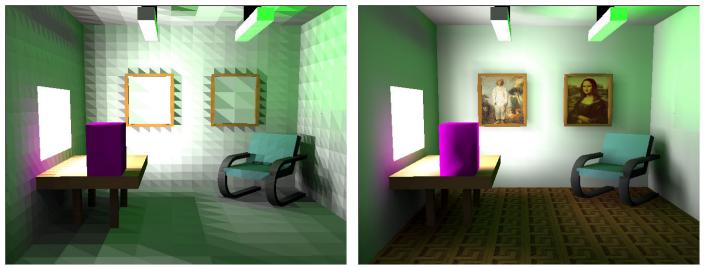
N

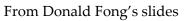
#### N equations and N unknown variables



# **Radiosity Algorithm**

- Subdivide the scene in small polygons
- Compute a constant illumination value for each polygon
- Choose a viewpoint and display the visible polygon
  - Keep doing this process





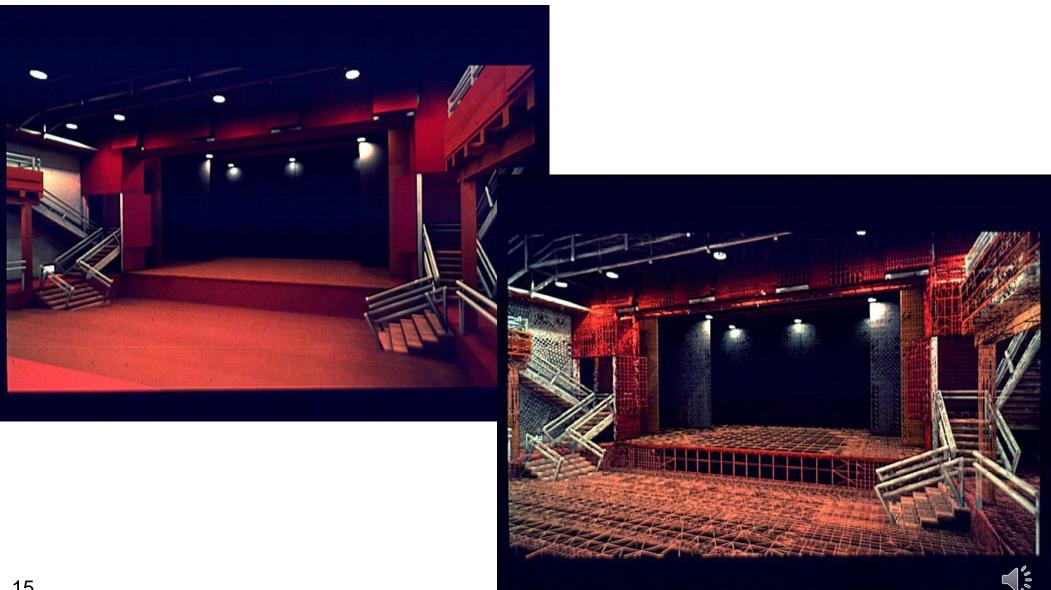


### **Radiosity Result**



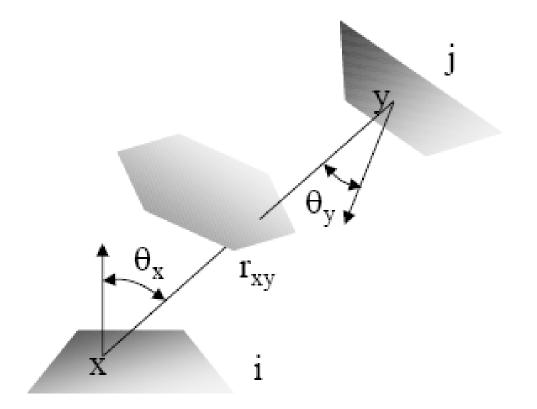


### **Theatre Scene**



### **Compute Form Factors**

$$F(j \to i) = \frac{1}{A_j} \int_{A_i A_j} \frac{\cos \theta_x \cdot \cos \theta_y}{\pi \cdot r_{xy}^2} \cdot V(x, y) \cdot dA_y \cdot dA_x$$



## **Radiosity Equation**

• Radiosity for each polygon *i* 

$$B_i = B_{e,i} + \rho_i \sum_j B_j F(i \to j)$$

#### Linear system

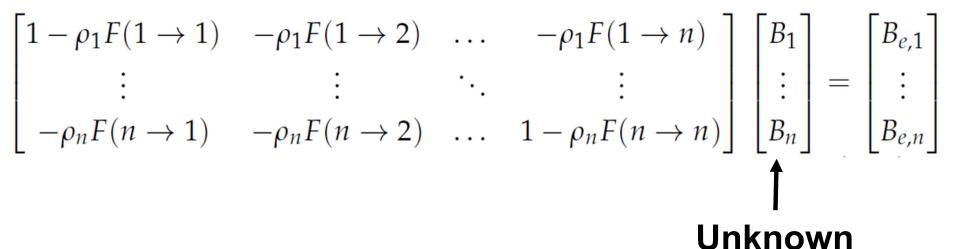
- B<sub>i</sub> : radiosity of patch i (unknown)
- B<sub>e,i</sub> : emission of patch i (known)
- ρ<sub>1</sub> : reflectivity of patch i (known)
- F(i→j): form-factor (coefficients of matrix)



## Linear System of Radiosity

#### Known

#### Known





## How to Solve Linear System

- Matrix inversion
  - Takes O(n<sup>3</sup>)
- Gather methods
  - Jacobi iteration
  - Gauss-Seidel

### Shooting

Southwell iteration



### **Iterative Approaches**

### Jacobi iteration

- Start with initial guess for energy distribution (light sources)
- Update radiosity of all patches based on the previous guess

$$B_i = B_{e,i} + \rho_i \sum_j B_j F(i \to j)$$

$$f = B_{e,i} + \rho_i \sum_j B_j F(i \to j)$$
Iew values Old values

- Repeat until converged
- Guass-Seidel iteration

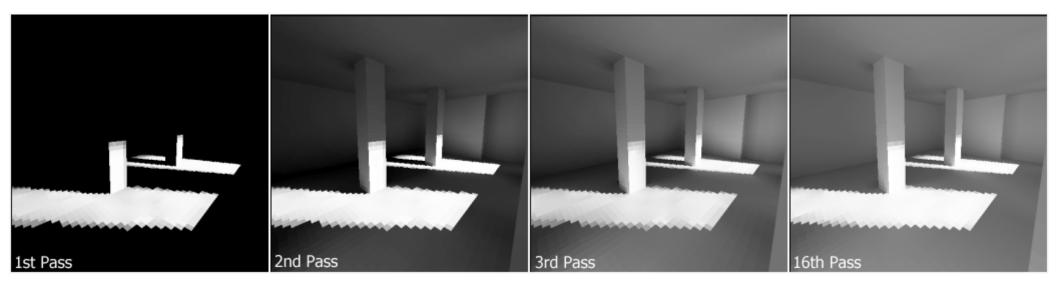
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• New values used immediately



### **Progress of Update Steps**

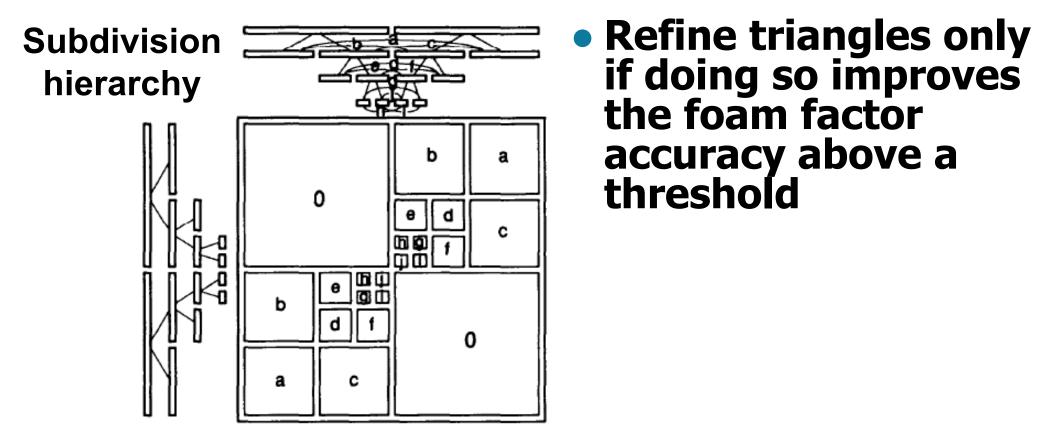
#### Update step supports the light bounce





### **Multi-Resolution Approach**

#### • A Rapid Hierarchical Radiosity Algorithm, Hanrahan, et al, SIGGRAPH 1991



Block diagram of the form factor matrix



# **Hybrid and Multipass Methods**

### Ray tracing

- Good for specular and refractive indirect illumination
- View-dependent

### Radiosity

- Good for diffuse
- Allows interactive rendering
- Does not scale well for massive models

### Hybrid methods

• Combine both of them in a way

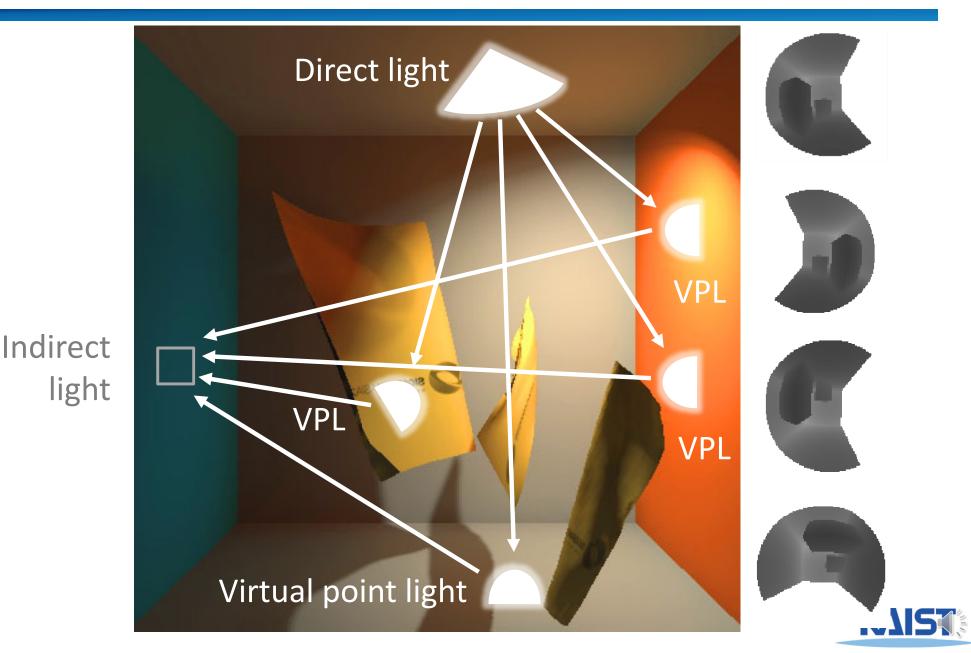


### **Instant Radiosity**

- Use the concept of radiosity
- Map its functions to those of classic rendering pipeline
  - Utilize fast GPU
- Additional concepts
  - Virtual point lights
  - Shadow maps



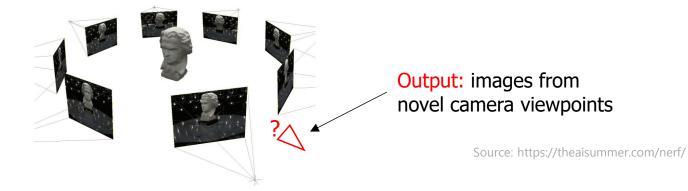
### **Instant Radiosity**



#### NeRF: Neural Radiance Fields ECCV 2020 Oral - Best Paper Honorable Mention

The goal of NeRF is to synthesize photorealistic images from novel camera viewpoints.

Input: images from various camera viewpoints



Examples (synthesized from novel views)





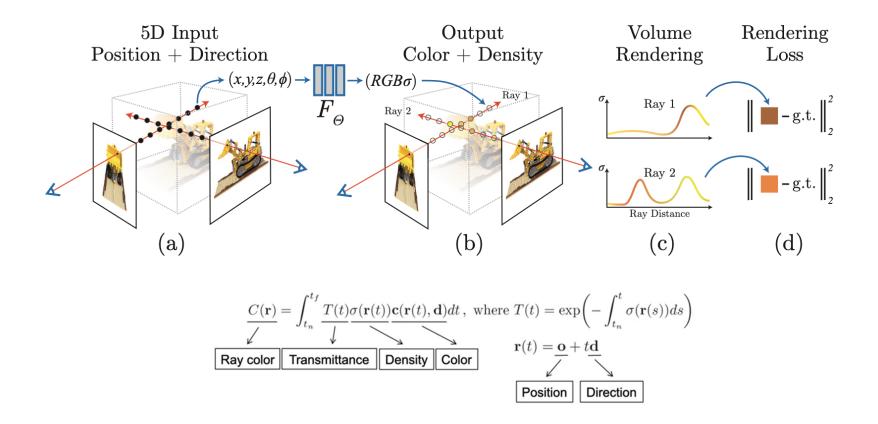




KAIST

https://www.matthewtancik.com/nerf

#### Neural Radiance Fields ECCV 2020 Oral - Best Paper Honorable Mention



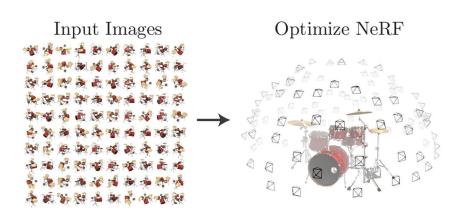


NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020

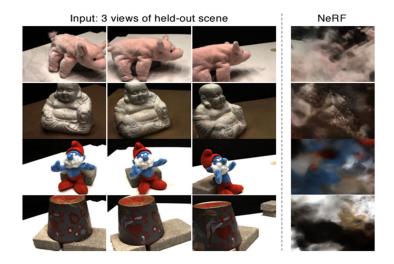
#### Cons of NeRF

#### **Requires Dense camera viewpoints**

**Since NeRF is under-constrained** it produces blurred or distorted results with sparse-view inputs. => Learning accurate 3D representation of an object requires dense views.



Dense camera viewpoints are required (e.g., 50+ source images)





pixelNeRF: Neural Radiance Fields from One or Few Images, CVPR'21

### **Class Objectives were:**

### Understand radiosity

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### Homework

- Go over the next lecture slides before the class
- Watch 2 paper videos and submit your summaries every Mon. class
  - Just one paragraph for each summary

#### **Example:**

Title: XXX XXXX XXXX

Abstract: this video is about accelerating the performance of ray tracing. To achieve its goal, they design a new technique for reordering rays, since by doing so, they can improve the ray coherence and thus improve the overall performance.



 Title: One Noise to Rule Them All: Learning a Unified Model of Spatially-Varying Noise Patterns

**Conference: SIGGRAPH 2024** 

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This work allows generating procedural noise (that is coherent) that uses different noise algorithms and parameters at different parts of the image. This means that we can generate Perlin noise on the left side, Voronoi noise on the right side, and have them blend together from left to right. They achieved this by training a diffusion model that is conditioned on the noise parameters on each part. They were able to train this model without having a reference of how to blend the Perlin/Voronoi example above by creating training data by copy and pasting different noise images on top of the second se  NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020 Oral

**NeRF** generates volumetric object from 2D images that is obtained from diverse camera positions. From the 5 dimensional coordinates by using deep neural networks it estimates Rgb value that corresponds to the coordinates. Since volumetric rendering is differentiable, it is required to have images with known camera poses. Furthermore the paper explains how to optimize neural radiance field to render realistic view with sophisticated geometry ist

## **Any Questions?**

- Submit four times in Sep./Oct.
- Come up with one question on what we have discussed in the class and submit at the end of the class
  - 1 for typical questions
  - 2 for questions that have some thoughts or surprise me



### **Next Time**

#### Radiometry and rendering equation

