

Lecture 23: Image-based Modeling and Lighting

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Announcements

- Projects: Email short (1-2 paragraphs)
update on project by next Tuesday
 - Plans till project due date

Complexity

- Lighting: many lights, environment maps
 - Global illumination, shadows
- Materials: BRDFs, textures
- Geometry: Level-of-detail, point-based representations
- All: image-based rendering

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Image-based Modeling

- Extract geometry + textures from pictures
 - Create a simple model
- Reuse geometry and texture to render scene from new viewpoints
- Façade system:
 - Debevec and Malik, UCB

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Match Edges

- Start from photograph of building
- User creates rudimentary model with cubes
- Marks corresponding edges between model and photographs
- Enough correspondences to reconstruct camera and model parameters



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Use blocks

- Easy to specify
- Fewer interactions
- Easy to determine final surface

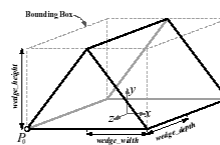
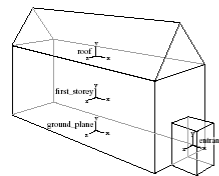
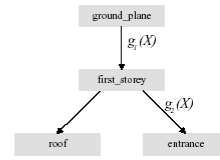


Figure 3: A wedge block with its parameters and bounding box.



(a)



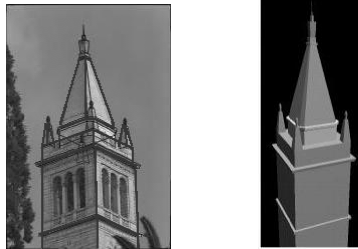
(b)

Figure 4: (a) A geometric model of a simple building. (b) The model's hierarchical representation. The nodes in the tree represent parametric primitives (called blocks) while the links contain the spatial relationships between the blocks.

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Find best fit

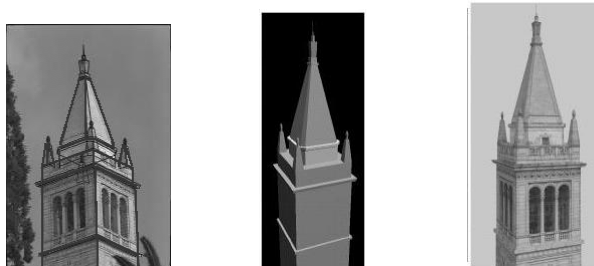
- Project model representation to camera
- Create error term
- Minimize error
- Iterative method updates model representation and looks for best fit
- Also solves for camera parameters



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Extract textures

- Extract textures from original photograph
- Project them onto the surface



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View-dependent texture mapping

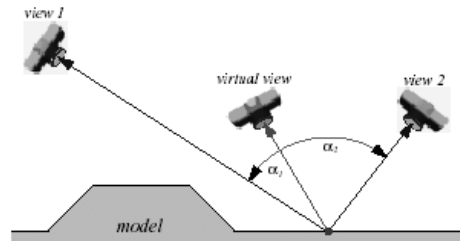


Figure 12: The weighting function used in view-dependent texture mapping. The pixel in the virtual view corresponding to the point on the model is assigned a weighted average of the corresponding pixels in actual views 1 and 2. The weights w_1 and w_2 are inversely proportional to the magnitude of angles α_1 and α_2 . Alternately, more sophisticated weighting functions based on expected foreshortening and image resampling can be used.

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Example: Extract Geometry



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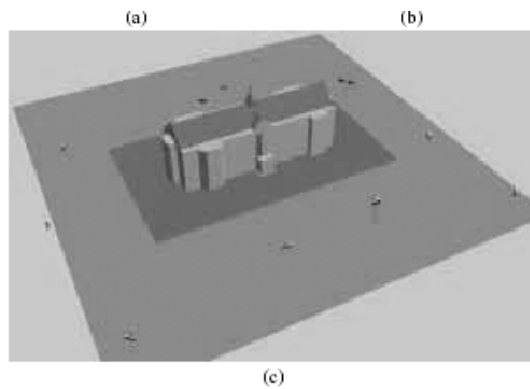


Figure 8: *The high school model, reconstructed from twelve photographs. (a) Overhead view. (b) Rear view. (c) Aerial view showing the recovered camera positions. Two nearly coincident cameras can be observed in front of the building; their photographs were taken from the second story of a building across the street.*

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Example: Final Model w/ Textures



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Used in the Matrix



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IBM Discussion

- Cons:
 - Small geometric details not included in model
 - primitives represented by the user are limited
 - Features in textures not part of model
 - Fair amount of manual input required!
- Pros:
 - Effective and useful
 - RealViz, ...
 - Open area of research

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Cons of IBM

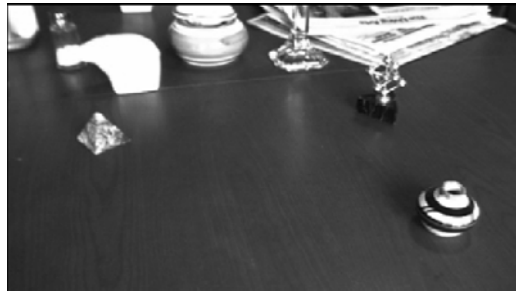
- Reasonable image quality but
 - Lighting is baked in: to undo lighting need material properties
 - Geometry is fixed



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Image Based Lighting

- Real Scene

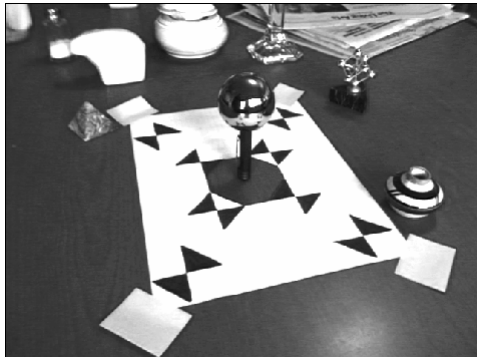


- Goal: place synthetic objects on table

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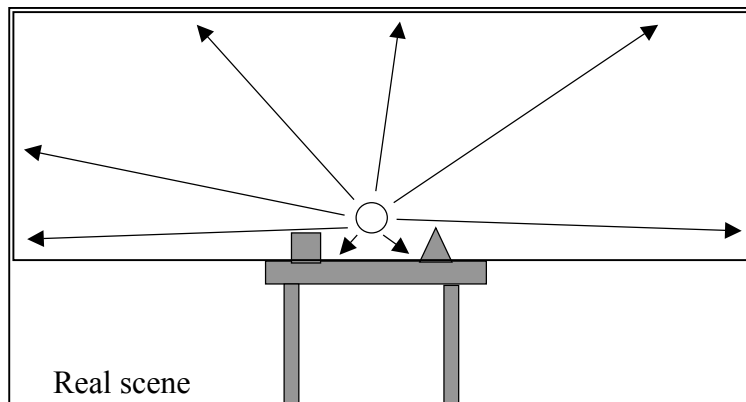
Image Based Lighting

- Capture illumination using illumination sphere



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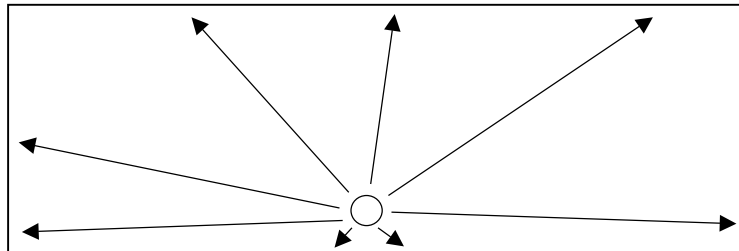
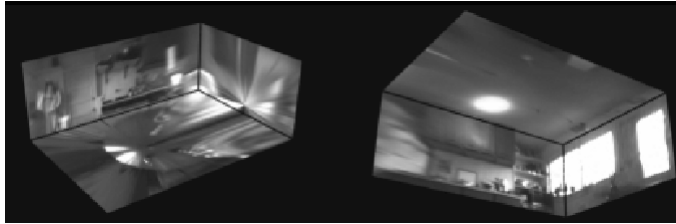
Image Based Lighting



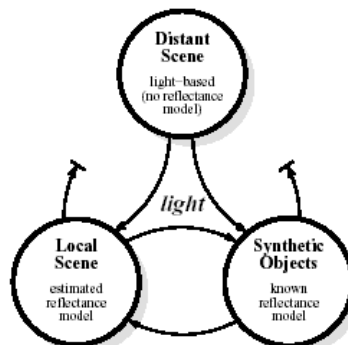
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Image Based Lighting

captured illumination field



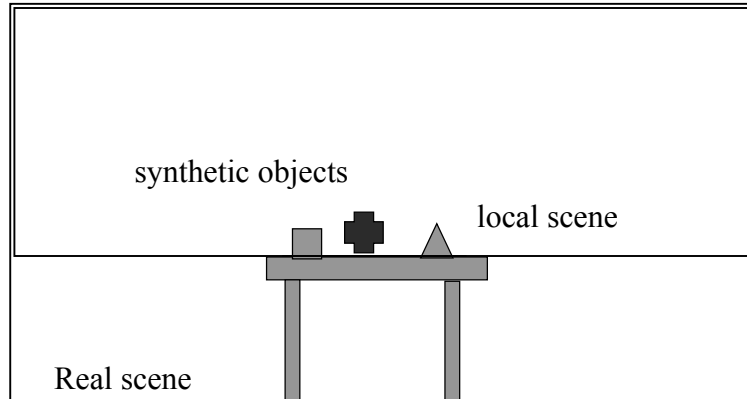
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Image Based Lighting

light based model

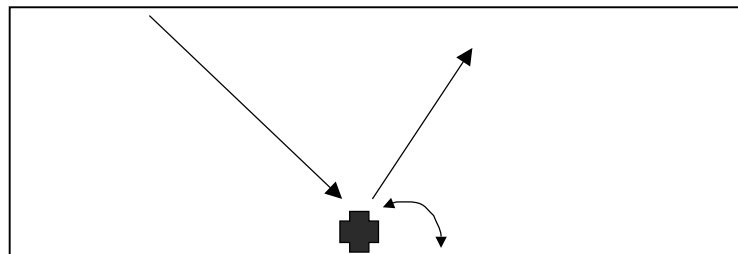


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Image Based Lighting

- Use renderer - compute effects of synthetic objects on local scene

light based model



synthetic objects (BRDF known) local scene (BRDF estimated)

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Image Based Lighting

- Render into the scene

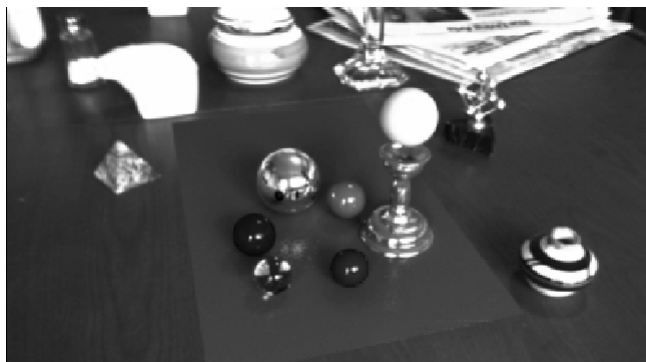


background

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Image Based Lighting

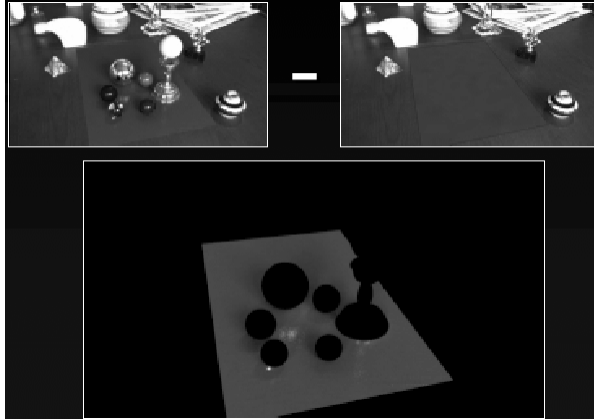
- Render synthetic objects



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Image Based Lighting

- Effect of local scene on real scene



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Image Based Lighting

- Add differences to image



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Discussion

- Good results for special effects
- But, estimating reflectances problematic

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Inverse global illumination

- Goal: recover BRDF per patch
- But account for GI in an interior environment

- Idea: solve for Ward BRDF model
 - specular parameters uniform per patch
 - diffuse interreflection handled trivially
 - specular interreflection (rare) handled by simple iterative algorithm

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Handling interreflection

- In diffuse case, all is easy
 - each patch lit by sources and other patches

$$B_i = E_i + \rho_i \sum_j B_j F_{ij}$$

- Specular case is more tricky
 - illum. depends on specular parameters elsewhere
 - assuming diffuse dominates, iteratively solve for a correction for specular illumination
 - (note: must observe a highlight on every surface)

$$L_i = \left(\frac{\rho_d}{\pi} + \rho_s K(\alpha, \Theta_i) \right) I_i$$

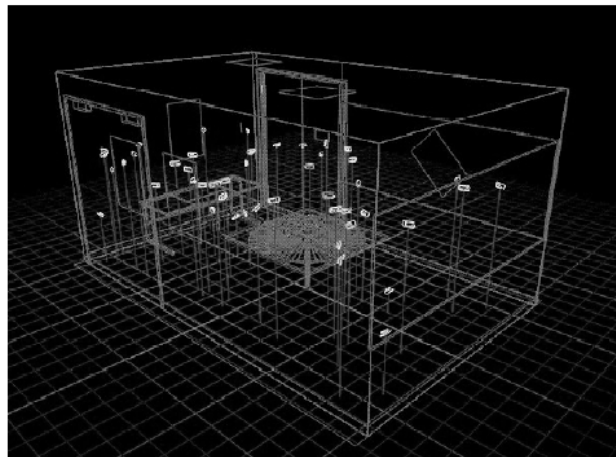
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IGI inputs



40 high-dynamic-range images

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IGI results



Re-rendered (bottom) to match input (top)

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IGI results



Re-rendered with new light (bottom) to match photos (top)

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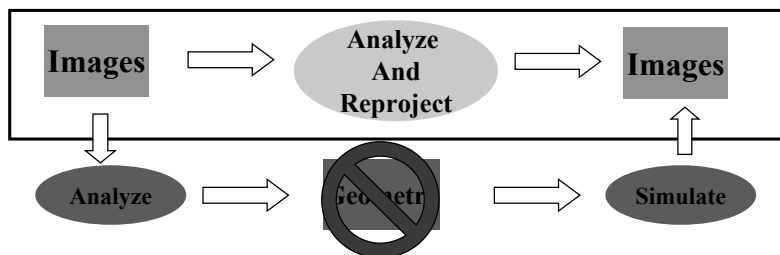
Summary of IBM, IBL

- Very powerful
- Many interesting research areas to be solved

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Image-based Approaches

- Goal: Realism!
- Image is input *and* rendering primitive



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Comparison

- No depth
 - QuickTime VR (simplest, 2D panoramas)
 - Lumigraph/Light Field (4D arrays)
- Reconstructed Depth
 - Plenoptic Modeling (2.5 D)
- IBM vs. IBR
 - Some manual user input ok
 - Simple geometry recovered with user assistance
 - Complex geometry represented as texture

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Conclusions

- IBR: promising approach to handle complexity
- Benefits:
 - No labor-intensive modeling
 - High geometric and material complexity
 - Rendering time constant: proportional to image size, independent of scene complexity
- Disadvantages:
 - Quality
 - Not-quite automatic

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- Exam: Everything till today