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MANIFOLD NEXT EVENT ESTIMATION

# **Motivation**

- we're making movies
- occasionally there is water/sweat/tears/blood on character
- high variance due to specular-diffuse-specular!



# Motivation

canonical specular-diffuse-specular (SDS) scenario, transmissive case:



# **Metropolis light transport (Kelemen style)**

- simplified to canonical test case for better study
- > 3min/frame render, no motion blur. temporal inconsistency!



# **Metropolis light transport (improved HSLT)**

- better stratification due to explicit handling of ray differentials
- still problems discovering individual effects (path configuration and sub-spaces)!



# The challenge:

- 1. leverage HSLT perturbations **without** the MLT **noise**
- 2. help HSLT **discover** good initial paths more quickly

sample a path X by perturbing an initial seed path Y

 $\triangleright$  what is the probability density function p(X)?

$$p(\boldsymbol{X}) = \int p(\boldsymbol{X}|\boldsymbol{Y})p(\boldsymbol{Y})d\boldsymbol{Y}$$

expensive integral! also cannot stochastically solve it (need to divide by PDF, not a linear operator, does not commute with expectation)

fastest approach: do not compute the integral!



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$$p(\mathbf{X}) = \int p(\mathbf{X}|\mathbf{Y})p(\mathbf{Y})d\mathbf{Y}$$

fastest approach: do not compute the integral:

deterministically enumerate all paths so we don't need the PDF (Accurate Computation of Single Scattering in Participating Media with Refractive Boundaries in the Wednesday session)



sample a path X by perturbing an initial seed path Y

 $\triangleright$  what is the probability density function p(X)?

$$p(\mathbf{X}) = \int p(\mathbf{X}|\mathbf{Y})p(\mathbf{Y})d\mathbf{Y}$$

fastest approach: do not compute the integral:

always consider pairs of paths (X, Y), so we only need p(X|Y)p(Y), not the marginalised distribution (Gradient-domain Bidirectional Path Tracing earlier on in this session)



sample a path X by perturbing an initial seed path Y

 $\triangleright$  what is the probability density function p(X)?

$$p(\mathbf{X}) = \int p(\mathbf{X}|\mathbf{Y})p(\mathbf{Y})d\mathbf{Y}$$

fastest approach: do not compute the integral:

> make sure there is only a single  $Y_0$  and  $p(X|Y) = \delta_X(Y - Y_0)$ (this paper)



# 2. Observation: thin glass approximation is not that bad

- start from this as a seed path Y (dashed line)
- > use same machinery as half vector space light transport (earlier in this session) to repair the path
- $\triangleright$  in fact, Y is not a valid transport path, only accumulate admissible path X



# **Overview: Manifold Next Event Estimation**

- $\triangleright$  start from thin glass approximation Y
  - $\triangleright$  perturb using half vector sampling + Newtonian walk to find admissible path X
  - same machinery as half vector space light transport/manifold exploration
- integrate into path space framework with multiple importance sampling, provide
  - 1. sampling of a new path
  - 2. evaluation of the probability density function
  - 3. evaluation of the measurement contribution

# 1. Sampling a new path X

 $\triangleright$  sample point  $x_c$  on light source and create seed path Y

- $\blacktriangleright$  sample half vector  $h_3$ , remember PDF in half vector space
- $\triangleright$  run (deterministic) Newtonian walk to find admissible path X
- compute (simplified) measurement contribution in half vector space



# 2. Evaluate the PDF of a path X (constructed e.g. via path tracing)

- compute PDF of light source vertex and create seed path Y
- evaluate PDF of half vectors in half vector space
- $\triangleright$  run newtonian walk to create tentative admissible path X'
- $\triangleright$  check for convergence to the right path, here  $X' \neq X$  so have to return 0
- convert PDF from half vector space to vertex area measure



# 3. Evaluate the measurement contribution

- compute the simplified measurement in half vector space (cf. IHSLT talk earlier on),
- and use along with PDF in half vector space for Monte Carlo estimator:

$$I_j \approx \frac{1}{N} \sum \frac{f(X)}{p(H)} \left| \frac{dX}{dH} \right|$$

 $\geq$  compute |dX/dH| explicitly to convert PDF to vertex area measure (see paper)

connection of |dX/dH| to ``ray differential'' term D in Accurate Computation of Single Scattering in Participating Media with Refractive Boundaries, but also works for rough interfaces!

path tracing

1040 spp PSNR 12.0



path tracing with next event estimation

562 spp PSNR 19.9



bidirectional path tracing

432 spp PSNR 20.0



half vector space light transport

529 spp PSNR 33.6



#### Manifold Next Event Estmation

244 spp PSNR 35.3



# **Firefly removal (biased)**

outliers come in fact from PT, not MNEE!

detect robustly: change MIS weights if MNEE pdf is unexpectedly zero (PSNR 35.3 -> 37.9)



# **Results: temporal stability**

we can use low discrepancy point sets (Halton here)



# Conclusion

- introduced an interesting new framework how to sample paths:
  - discover certain transmitted caustics reliably at first sampling attempt
  - explore with half vector space machinery, but without MLT
- some limitations on which paths can be discovered (see paper for all the details)
- lightweight on memory
- only used where necessary, can be combined with other techniques via MIS
- fast if pixel coverage of difficult transport is small
- details (such as about multi-layer materials) in the paper

thank you for listening!

# backup slides

# **Photon mapping/VCM**

- Vertex Connection and Merging shoots photons just to bounding box of head
  - still inefficient at finding small caustics
  - high storage and kd-building overhead
  - photon paths get lost in hair: expensive tracing, no contribution







# Measurement and discontinuous normal derivatives



Figure 9: Bias introduced by non  $C_2$  continuous geometry: since the normal derivatives are part of the measurement contribution in half vector space via the transfer matrix in Eq. (6), approximate derivatives will lead to approximate path contributions. This requirement to the renderer is shared between manifold exploration, HSLT, and MNEE. Note that the tessellation here is purposefully extremly poor. Continuous normal derivatives can be achieved e.g. by using PN triangles [VPBM01].

## **Displaced geometry**

reference (KMLT, 1kspp) MNEE HSLT MNEE HSLT HSLT MNEE 72spp 72spp

# Limitations

- ambiguous paths are not found (red paths)
  - there is a relevant range of cases where this does not happen! (dashed floor level)
- caustics outside the shape are only found to a limited extent
- works for rough surfaces, but less efficient at high roughness
- for detailed discussion see paper!

