Sampling and Reconstruction of Visual Appearance: From Denoising to View Synthesis

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Ravi Ramamoorthi

http://www.cs.ucsd.edu/~ravir

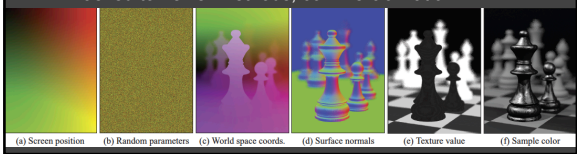
Feature-Space Methods

Monte Carlo Rendering (biggest application)

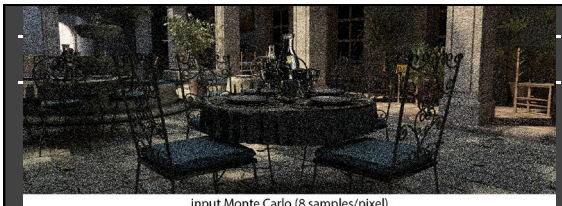
- General practical denoising (no frequency) [2012-]
- General effects (Sec 2.3 of EG STAR Report)
- General image-space denoising framework
- *But use auxiliary features (depth, normals, etc.)*
- Basis for methods deployed in industry today
- Students present 3 key papers today

Random Parameter Filtering

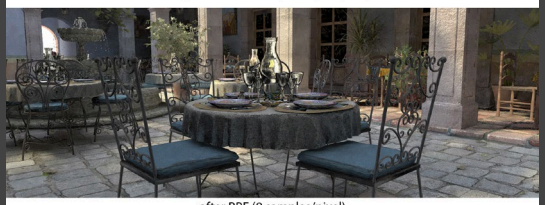
- Sen Darabi 12, importance of each feature
  - Addresses noisy features (e.g. depth of field)
  - Notion of mutual information
- Weighted bilateral filter, very good at low samples
  - Parameters determined by feature importance
  - Auxiliary features are key to beat image denoising
  - Has led to newer methods, commercialization



(a) Screen position (b) Random parameters (c) World space coords. (d) Surface normals (e) Texture value (f) Sample color



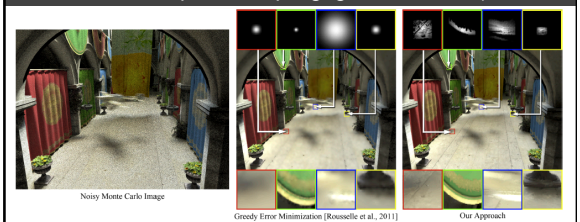
input Monte Carlo (8 samples/pixel)



after RPF (8 samples/pixel)

Subsequent Work

- SURE (Stein's unbiased risk estimator: general kernels, adaptive sampling, general effects) Li12



Noisy Monte Carlo Image | Greedy Error Minimization [Rousselle et al., 2011] | Our Approach

Figure 1: *Comparisons between greedy error minimization (GEM) [Rousselle et al. 2011] and our SURE-based filtering. With SURE, we are able to use kernels (cross bilateral filters in this case) that are more effective than GEM's isotropic Gassians. Thus, our approach better adapts to anisotropic features (such as the motion blur pattern due to the motion of the airplane) and preserves scene details (such as the textures on the floor and curtains). The kernels of both methods are visualized for comparison.*

Subsequent Work

- Moon et al. local linear or polynomial models, treat as regression. Many other methods
- APR: Polynomial order chosen to minimize error
- Newest methods use learning instead (later in course)

(a) Ours, 16 spp rMSE 0.00541 | (b) MC input, 16 spp rMSE 0.68832 | (c) Ours, 16 spp rMSE 0.00541 | (d) Reference, 32K spp