Fabric Appearance Benchmark

Sebastian Merzbach, Reinhard Klein

UNIVERSITÄT BONN

Introduction

How to evaluate your appearance modelling results?

- existing datasets & results often unavailable

⇒ most works only aim to reproduce appearance of their own measurements (usually new datasets)

$$E = \left\| \underbrace{\text{photo } I}_{\text{[LXR*18]}} - \underbrace{\text{rendering } \hat{I}}_{\text{[LXR*18]}} \right\|$$

⇒ only validations, but often no comparisons

- no code releases ⇒ high re-implementation effort
- other fields have standardized benchmarks: KITTI, Semantic3D, SUN RGB-D, Princeton Shape, ...
- no benchmarks for appearance modelling so far
- through standardized testing, benchmarks enable fair comparisons between existing and new works

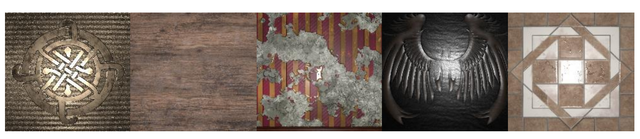
Benchmark Wishlist:

- real-world data
- versatile appearance ⇒ fabrics
- well-defined and accurate surface geometry
- posed as challenge for further participation incentive
- public leaderboard

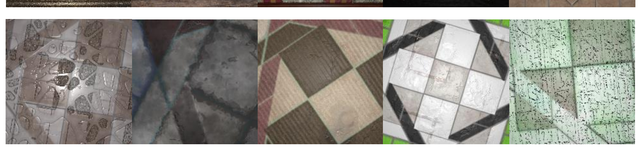
Related Work

Synthetic Data:

blended procedural SVBDFs [DAD*18], Adobe Stock SVBRDFs (Allegorithmic) on synthetic shapes [LXR*18]



procedural SVBRDFs, [DAD*18]



blended SVBRDFs , [DAD*18]

BRDF only:

MERL [MPBM03], OpenSurfaces [BUSB13], UTIA [FV14], SynBRDF [KGT*17], LIME [MMZ*18], EPFL RGL [DJ18]

Measured SVBRDFs:

UBOFAB19 [MHRK19]

Measured BTFs:

UBO14 [WGK14], UTIA [FKH*18]

BTFs, [WGK14]

fully released, no holdout sets ⇒ no fair challenge conditions

References

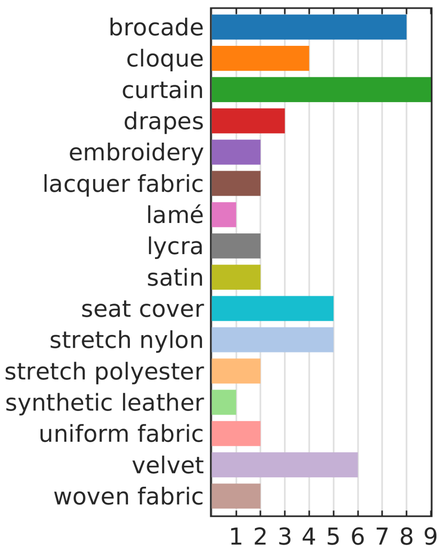
[BUSB13] Bell, Upchurch, et al.; OpenSurfaces: A Richly Annotated Catalog of Surface Appearance; TOG 32.24 (2013)
[DAD*18] Deschaintre, Aittala, et al.; Single Image SVBRDF Capture with a Rendering-Aware Deep Network; TOG 37.4 (2018)
[DJ18] Dupuy, Jakob; An Adaptive Paramteterization for Efficient Material Acquisition and Rendering; TOG 37.6 (2018)
[FKH*18] Filip, Kolafova, et al.; Evaluating Physical and Rendered Material Appearance; TVC (CGI 2018)
[FV14] Filip, Vavra; Template-Based Sampling of Anisotrpic BRDFs, CGF 33.7 (2014)
[KGT*17] Kim, Gu, et al.; A Lightweight Approach for on-the-fly Reflectance Estimation; ICCV (2017)
[LXR*18] Li, Xu, et al.; Learning to Reconstruct Shape and Spatially-Varying Reflectance from a Single Image; SIGASIA (2018)
[MHRK19] Merzbach, Hermann, et al.; Learned Fitting of Spatially Varying BRDFs; CGF 38.4 (2019)
[MMZ*18] Meka, Maximov, et al.; LIME: Live Intrinsic Material Estimation; CVPR (2018)
[MPBM03] Matusik, Pfister, et al.; A Data-Driven Reflectance Model; TOG 22.3 (2003)
[WGK14] Weinmann, Gall, Klein; Material Classification Based on Training Data Synthesized Using a BTF Database; ECCV (2014)

Dataset

Extension of UBOFAB19:

- 56 new fabrics
- acquisition: X-Rite TAC7
- radiometrically calibrated, registered HDR images
- per scan: 768 images:
  - 100 polychromatic point-lit
  - 388 panchromatic point-lit
  - 280 panchromatic line-lit

class distribution:



Overview with color highlights matching classes ↑

Public Release:

https://cg.cs.uni-bonn.de/appbench

Evaluation Set:

- 10% of poly- & panchromatic point-lit images
- only directional sampling publicly released

Evaluation

Standard Branch:

- participants evaluate their models on this sampling
- upload results to evaluation server
- automatic metric evaluation & ranking based on deviation of reconstructions $\hat{I}$ from measuremnts I

Local Branch:

- nonplanarity ⇒ nonlocal effects (shadowing, ...)
- reduce nonlocal effects with pixel confidences w_i

Metrics (M):

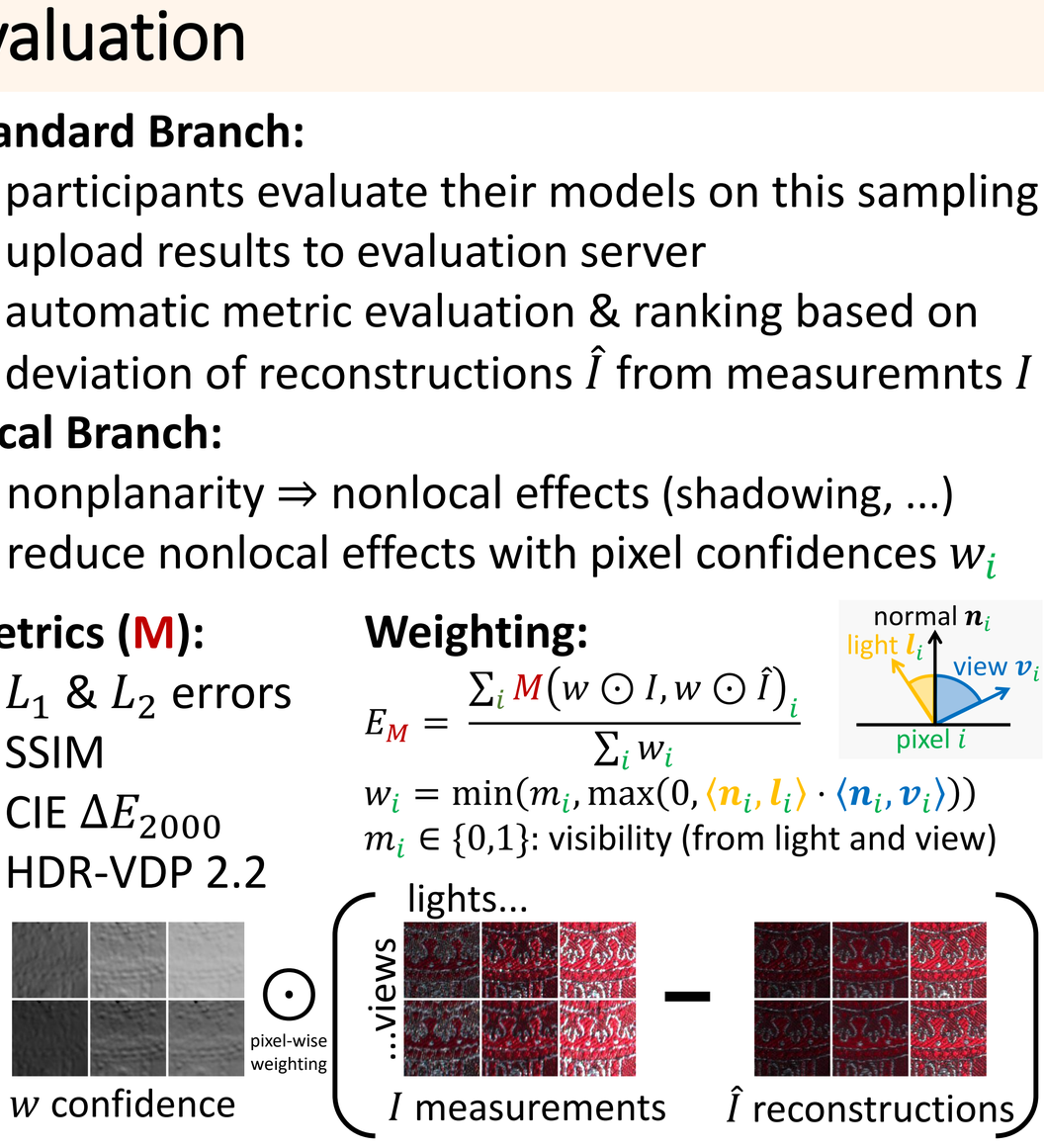
- L_1 & L_2 errors
- SSIM
- CIE ΔE_{2000}
- HDR-VDP 2.2

Weighting:

$$E_M = \frac{\sum_i M\left(w \odot I, w \odot \hat{I}\right)_i}{\sum_i w_i}$$

$$w_i = \min(m_i, \max(0, \langle \boldsymbol{n}_i, \boldsymbol{l}_i \rangle \cdot \langle \boldsymbol{n}_i, \boldsymbol{v}_i \rangle))$$

$m_i \in \{0,1\}$: visibility (from light and view)



Baseline Results

- X-Rite Pantora 1.6 SVBRDF fits
- single-lobe anisotropic SVBRDF
- spatially varying Fresnel term