SHAPE, APPEARANCE AND RELIGHTING FROM MULTI-LIGHT IMAGE COLLECTIONS

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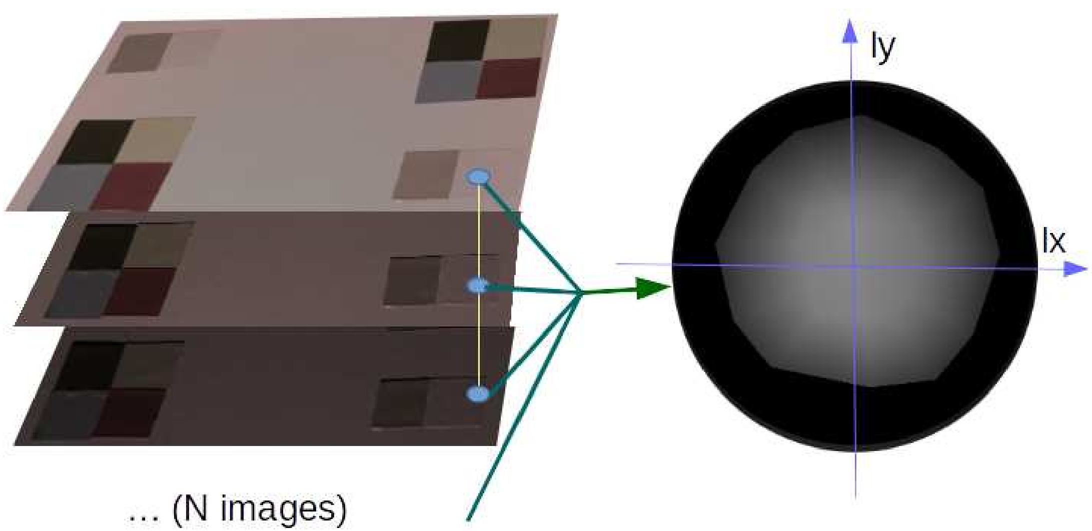
OVERVIEW

- MLIC
- Acquisition settings
- Light characterization
- Reflectance modeling/interpolation
- Photometric stereo
- Image enhancement/segmentation
- Discussion

MULTI LIGHT IMAGE COLLECTIONS

- Fixed camera/varying lights
- Popular capture setting for shape/reflectance analysis
  - Photometric stereo
  - BRDF estimation (known shape)
  - Visualization, e.g. offline (interactive) image based rendering with novel light conditions
  - Material analysis and segmentation



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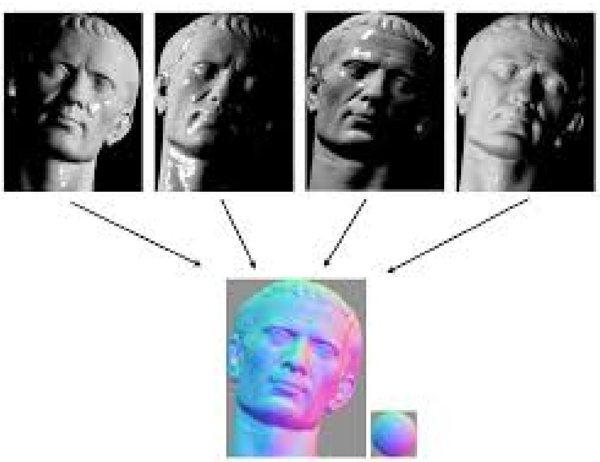
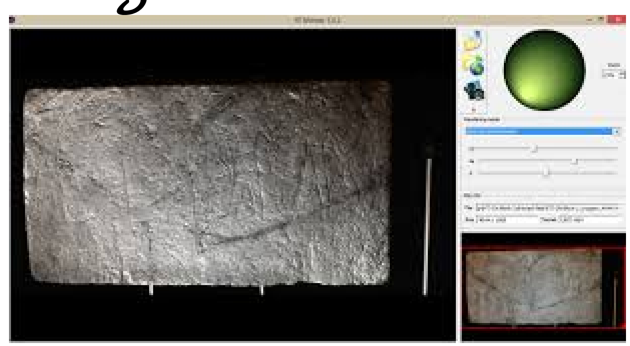




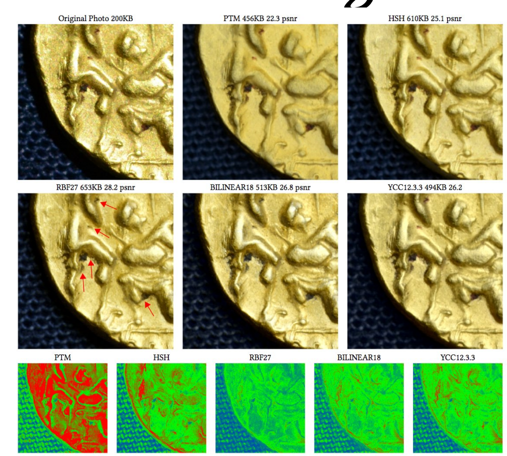
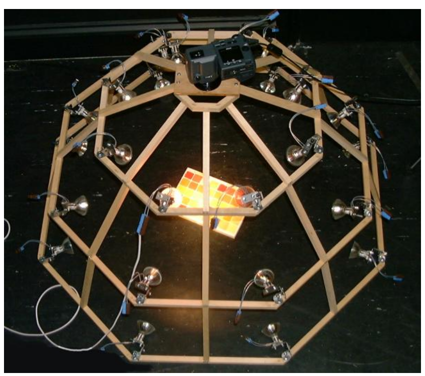


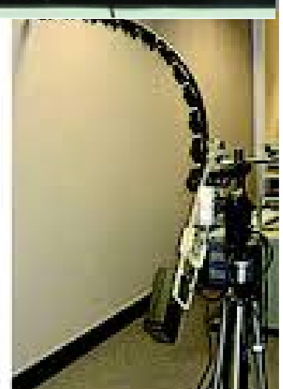
Figure 6: Visual comparisons. Original photograph (top-left). PTM, HSH, RBF27 and BILINEAR18 rendered from the same light direction. (Bottom) Color-coded RMSE (ranging from 0, blue, to 25, red). See more results at the project web page: http://vcg.isti.cnr.it/relight.

HOW TO ACQUIRE?

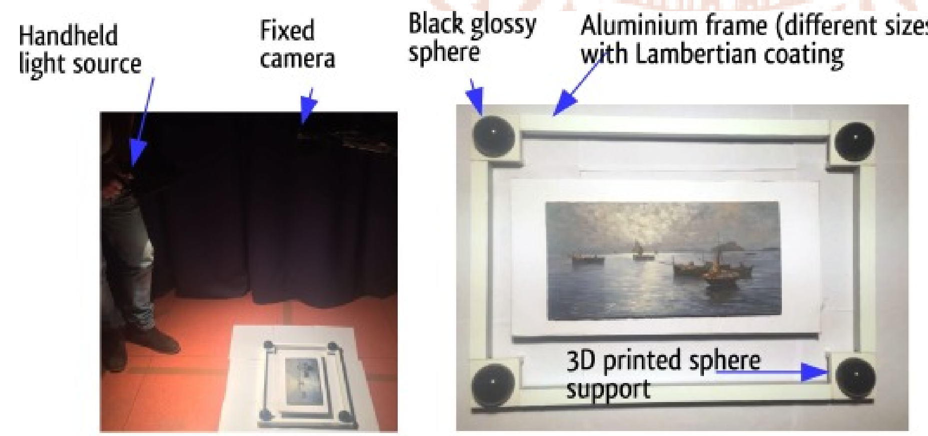
- Several practical setups in applicative contexts
- Two main choices
  - Handheld/freely movable light
  - Fixed dome solutions



(a)



(b)



(a) Setup (b) Scene

degrees of inclination from the horizon.

Figure 4: Field setup

Scan4Reco

CRS4

Multi-spectral RTI dome

November 2017

Horizon 2020
European Union funding
For Research & Innovation

Project funded by the Horizon'2020 in topic *Reflective-7*
Grant Agreement # 665091

FREEFORM ACQUISITION

Scan4Reco

CRS4

Free-form acquisition of calibrated RTI

November 2017

Horizon 2020
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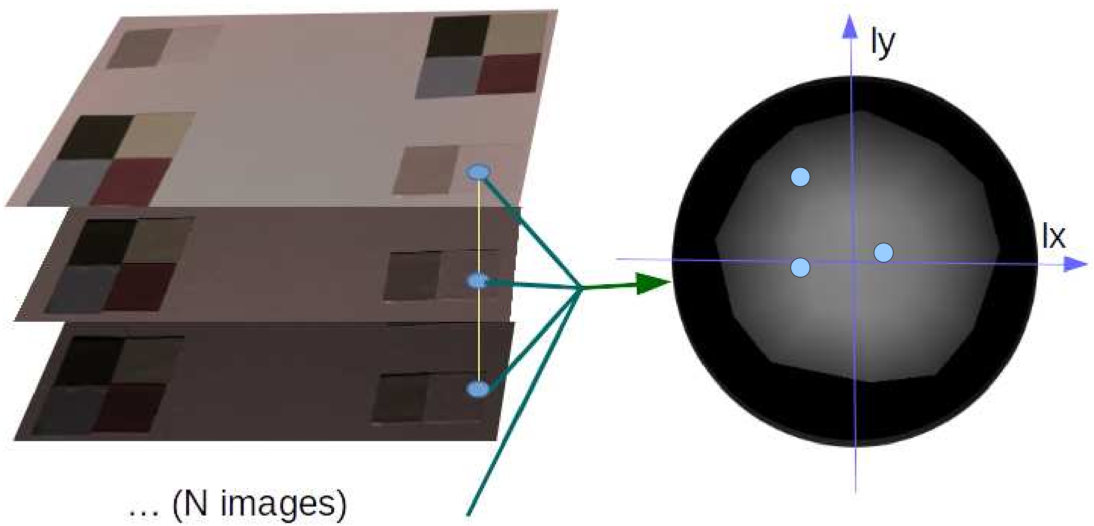
MLIC and BTF/BRDF capture

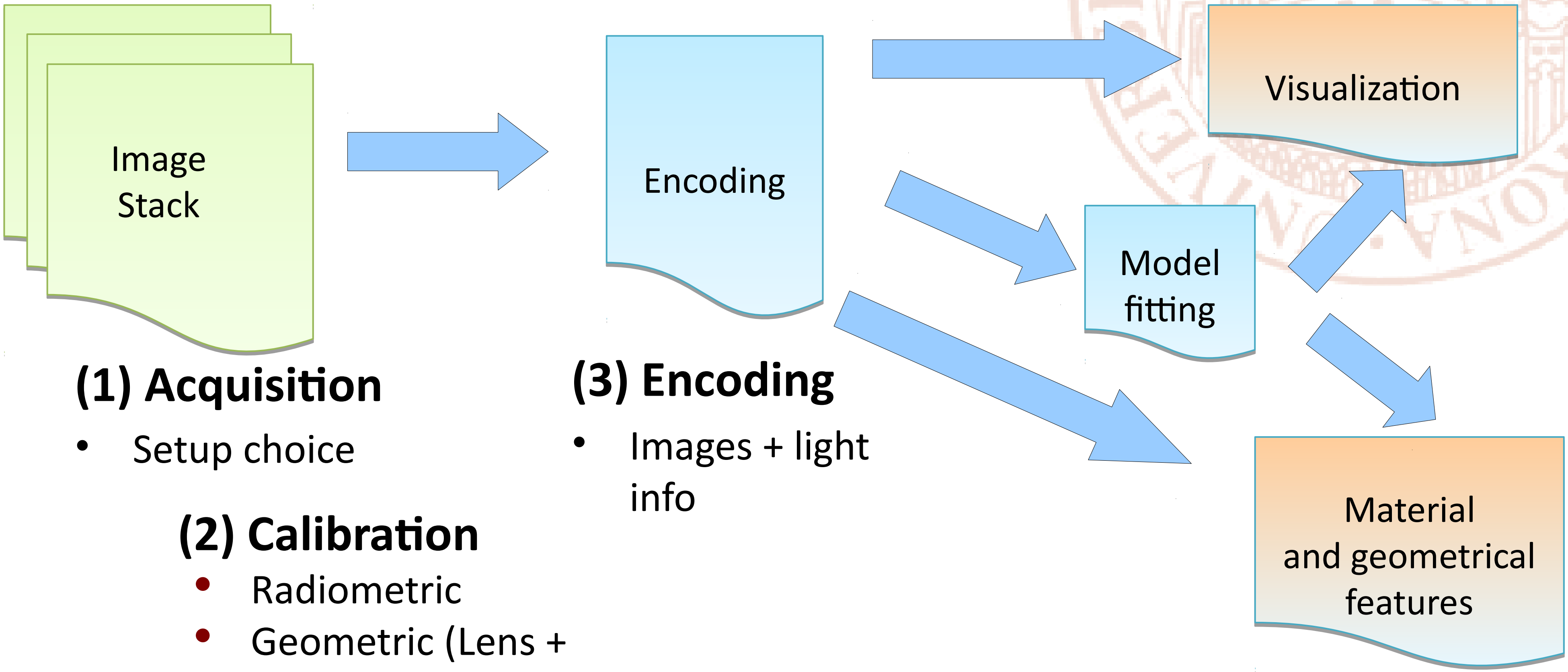
- MLIC capture only BRDF “slices”
- But have several practical applications
  - Cultural Heritage
  - Industry
  - Medical
  - Environment
- And peculiar issues to be solved that should be addressed
- We will se some of these issues
  - Calibration
  - Image based rendering/relighting
  - Robust reflectance fitting/photometric stereo

CAPTURED DATA

- N images with associated light directions
- For each pixel we get samples of a reflectance function (BRDF slice). We call this sampling "Appearance Profile"
- Setups capturing multiple views or rotating stages, adding possibly 3D scans can be used to derive full BTF information
- We will not address the processing of more complex data
  - We focus on issues of practical use of single view MLIC



PROCESSING PIPELINE



(1) Acquisition

- Setup choice

(2) Calibration

- Radiometric
- Geometric (Lens + extrinsics)
- Light direction
- Light Intensity

(3) Encoding

- Images + light info

(4) Interpretation

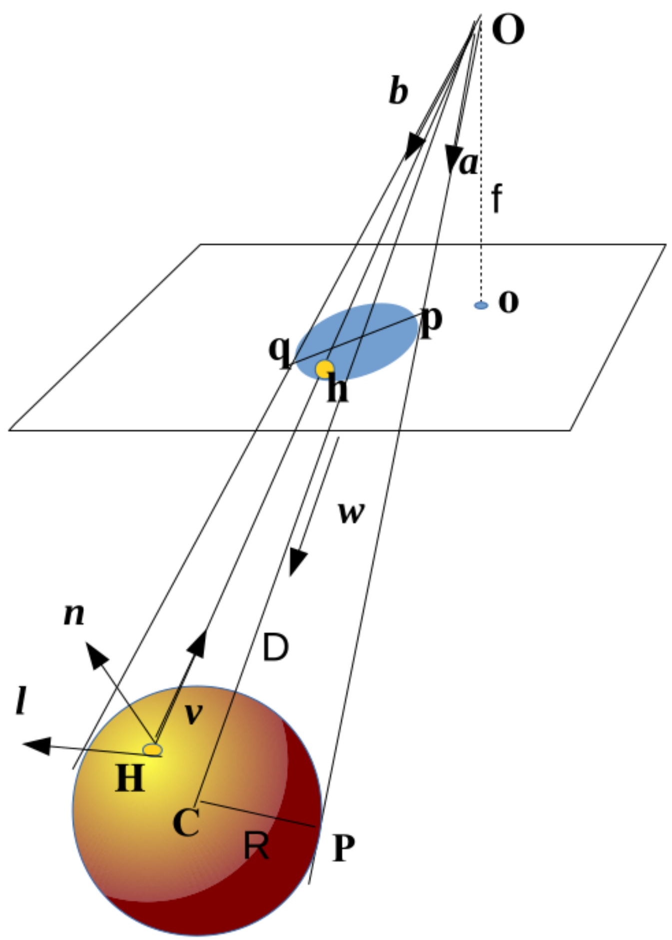
- Relighting
- Photometric Stereo
- Material characterization

CALIBRATION

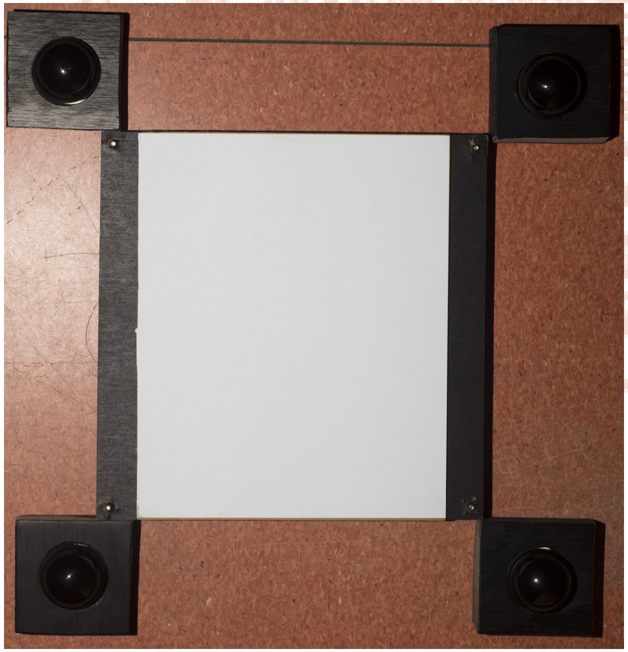
- Not easy in practical settings
- For our applications we assume known light (frequency, intensity, direction). But how can we know it?
- Simplifying hypotheses
  - Constant light direction (false)
  - Constant intensity (false)
  - Point light (false)
  - Known spot light shape (difficult)
  - Ortographic view (false)
- Most Photometric Stereo frameworks assume directional or point light, ortographic view [Ackermann 2015]

LIGHT DIRECTION ESTIMATION

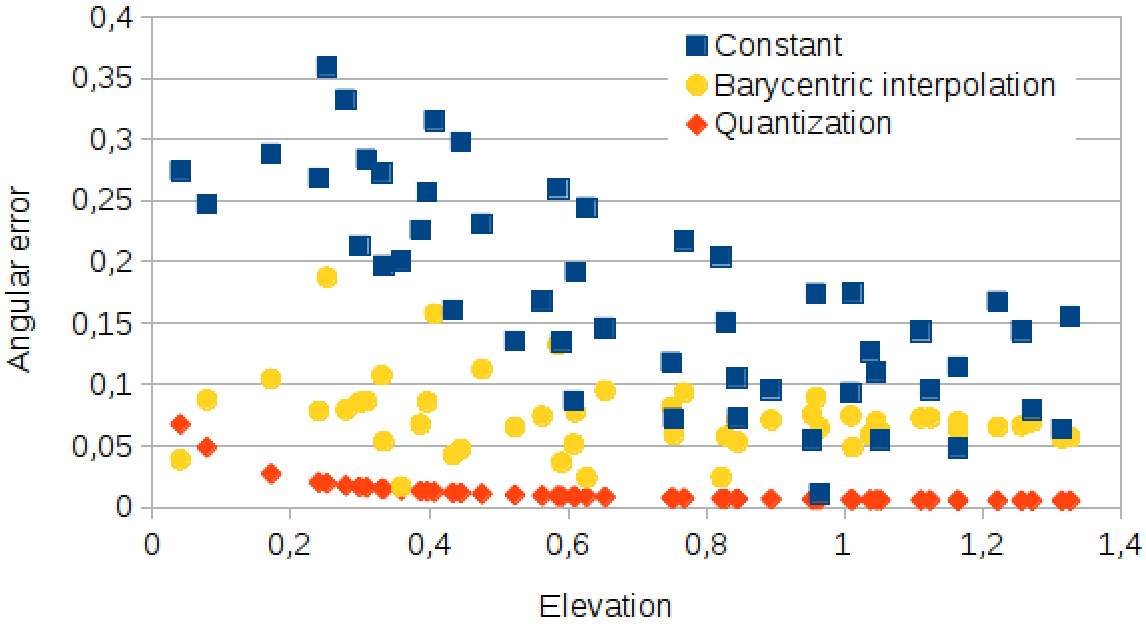
- Solutions
  - **Black reflective spheres**
  - Lambertian spheres
  - Lambertian planar target
  - Other (e.g. shadows)
- Detection of spheres masks
  - Circular if we assume ortographic view
  - Elliptic in general
- Highlight easily segmented
- Formulas to link highlight position and light direction
- Multiple spheres of known size gives possible point light location



EXPERIMENTAL EVIDENCE



- Large differences in light directions estimated on different spheres
- Constant approximation gives large errors for commonly used light sources [SPIE 2015]
- Two solutions
  - Accurate light beam modelling
  - Interpolation



Giachetti, A., et al. "Light calibration and quality assessment methods for Reflectance Transformation Imaging applied to artworks' analysis." Optics for Arts, Architecture, and Archaeology V. Vol. 9527. International Society for Optics and Photonics, 2015.

Light Beam Modelling

- Es. Pintus et al. 2016
  - Estimate light function given white planar targets

$$I(i,w) = \rho(w) \frac{L(i,w)}{d(i,w)^2} \left(\hat{l}(i,w) \cdot \hat{n}(w)\right)$$

  - Spotlight model

$$L(i,w) = L_0 \left(\hat{l}(i,w) \cdot \hat{a}(i)\right)^m$$

  - Solution by estimating axis per image, refining globally on the image set to obtain L_0 and m
- Ideally it is possible to measure light source properties
  - e.g. capturing multiple images at different distance and interpolating
  - Not widely used

Pintus, R., Ciortan, I., Giachetti, A., & Gobbetti, E. (2016). Practical free-form RTI acquisition with local spot lights.

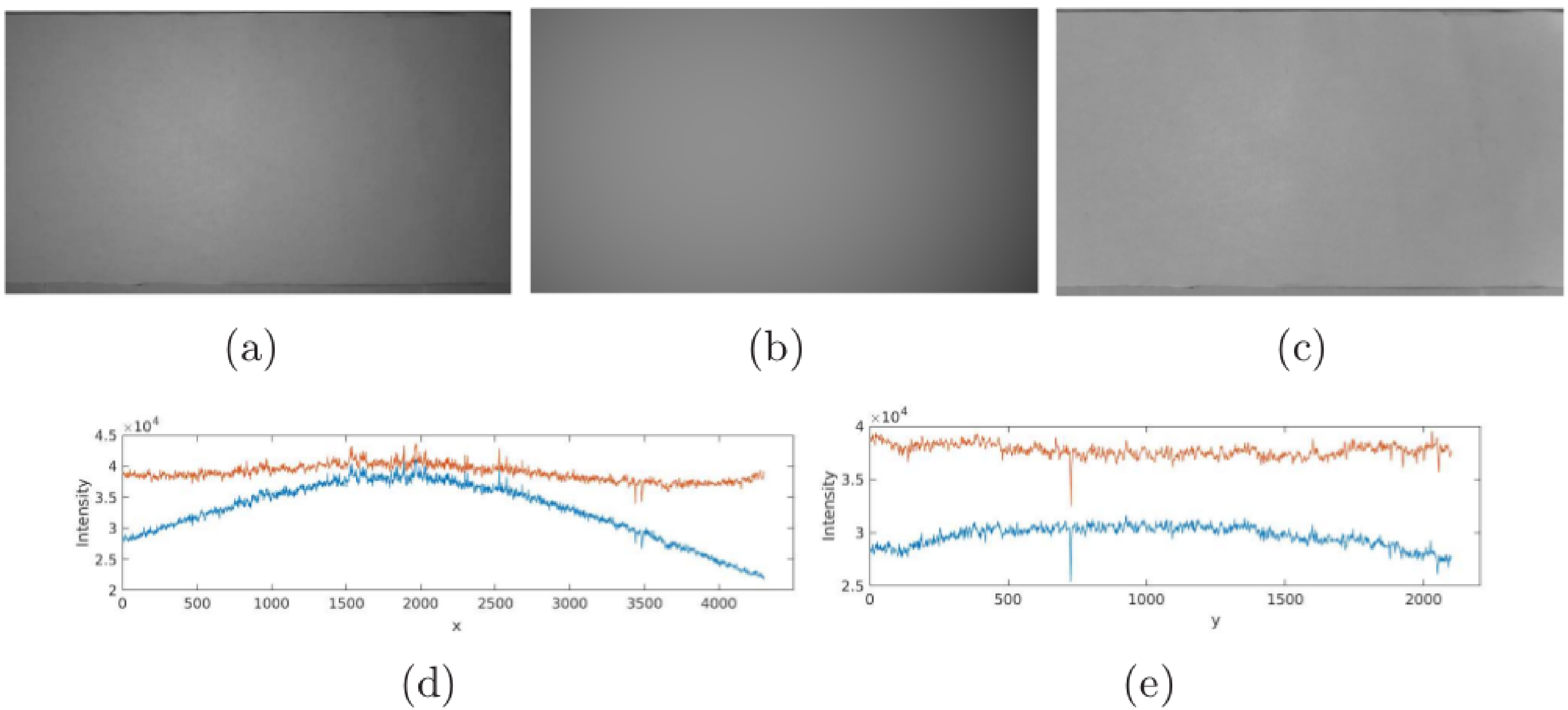
Calibration without light model

- We can neglect the use of a light model and correct the image making the illumination at each pixel location uniform
- Valid only on a plane, we should assume to acquire shapes only quite close to that plane
- Can correct both light inhomogeneities and lens vignetting
- Freehand acquisition:
  - Put Lambertian targets on the same plane around the object to be captured (e.g. a plane)
  - Interpolate the "white" background over the whole image
  - Normalize pixel values by mapping the corresponding white level to a reference value
- Dome acquisition
  - Pre-acquire calibration targets to determine the illumination everywhere in the "acquisition plane"

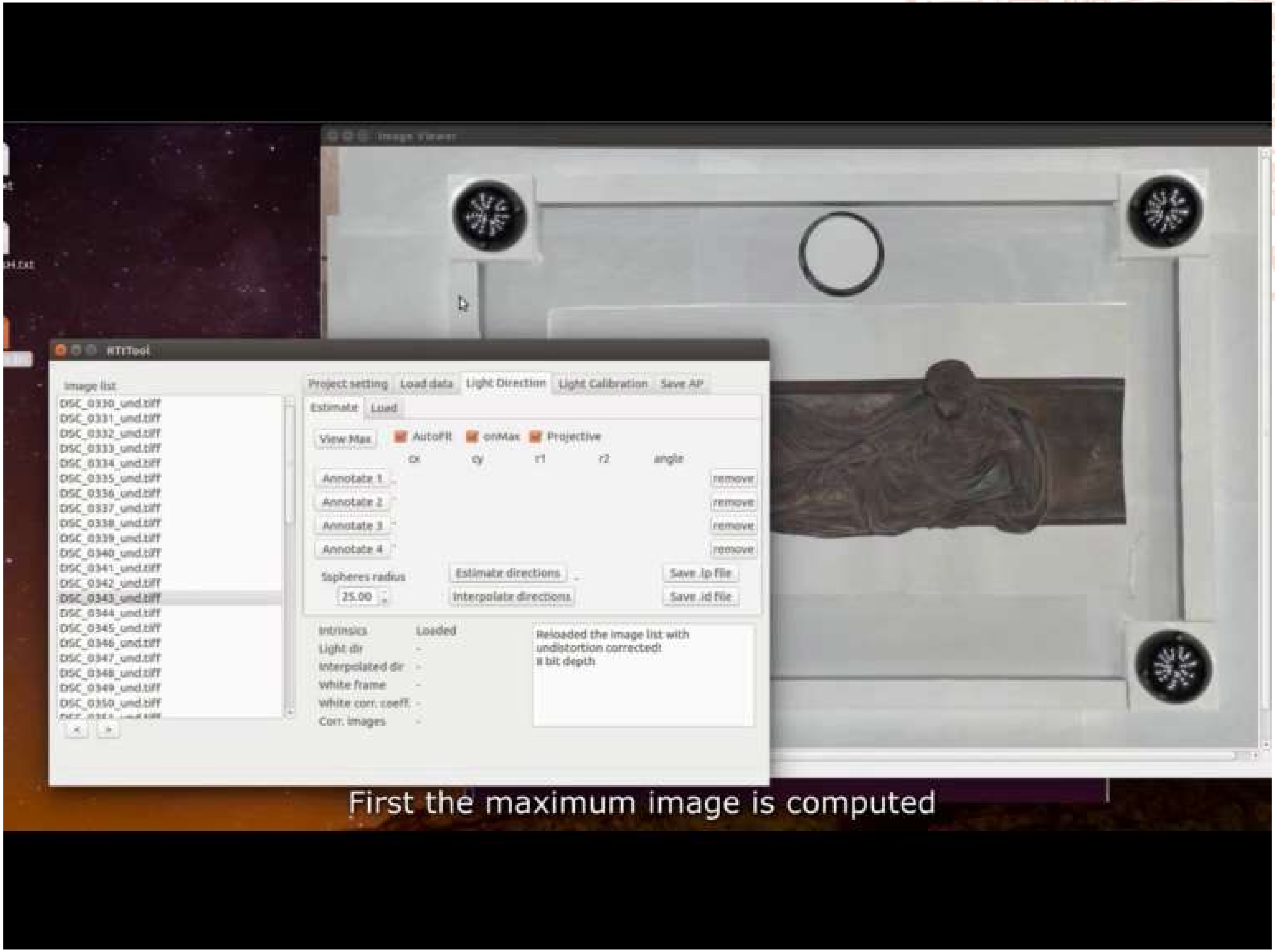
Giachetti, A., Ciortan,I.M., Daffara, C., Marchioro, G., Pintus, R., Gobbetti, E. A novel framework for highlight reflectance transformation imaging. Computer Vision and Image Understanding, 2018

DIRECT PLANAR/TARGET BASED CORRECTION

- Freehand acquisition: correctly equalized with frame
  - We need to assume that the acquired object is approximately on the plane



FREEFORM CALIBRATION



DOME CALIBRATION

Scan4Reco

CRS4

Multi-spectral RTI dome

Tutorial: data calibration with RTITool

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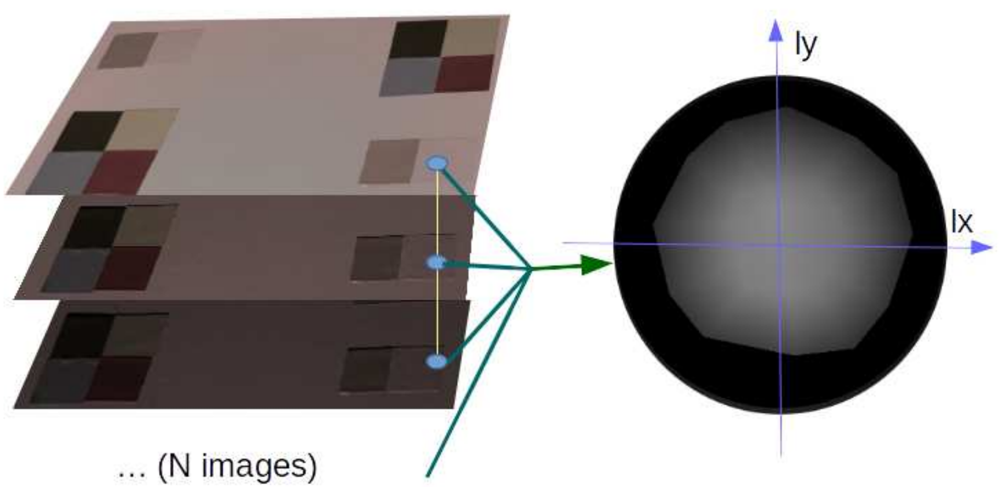
USE OF MLIC: REFLECTANCE FUNCTIONS FITTING AND RELIGHTABLE IMAGES

- The typical Cultural Heritage use of MLIC consists of generating relightable images by fitting simple reflectance functions over AP data
- Typical solutions: Polynomial Texture Maps, Hemispherical Harmonics
- Framework called typically "Reflectance Transformation Imaging" (RTI)
  - http://culturalheritageimaging.org/Technologies/RTI/

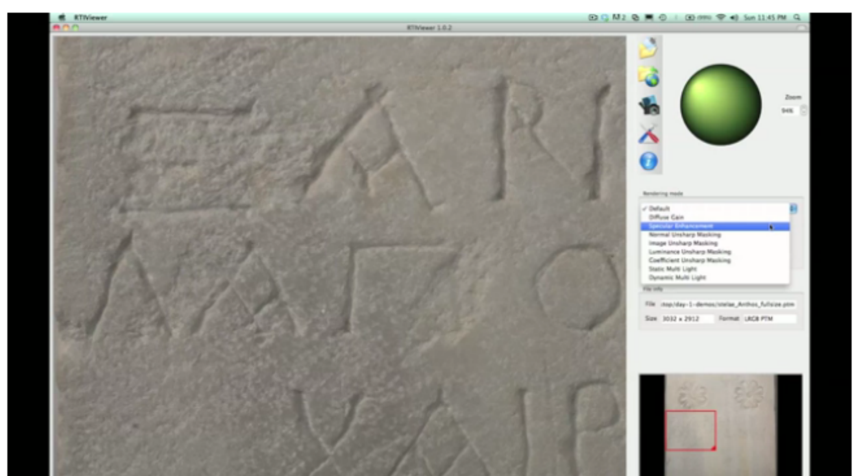


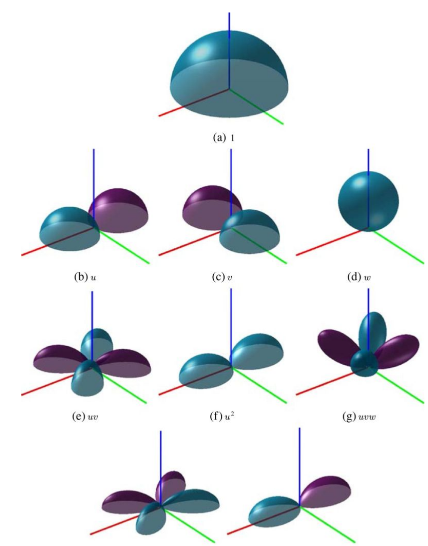
Polynomial Texture Maps

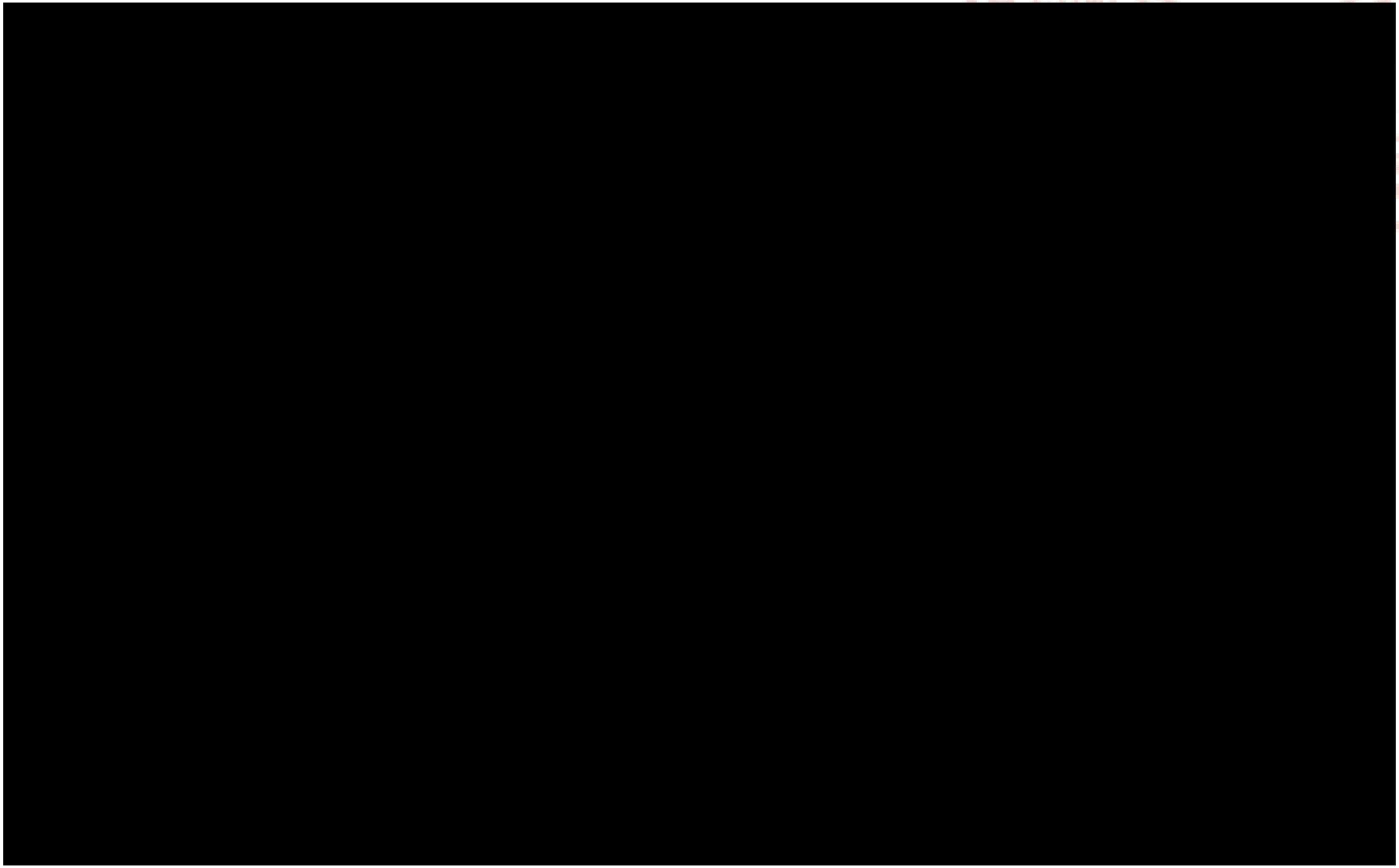
- PTM [Malzebender 2001] fit of polynomial function over AP data

$$L(u,v;l_u,l_v) = a_0(u,v)l_u^2 + a_1(u,v)l_v^2 + a_2(u,v)l_u l_v + a_3(u,v)l_u + a_4(u,v)l_v + a_5(u,v)$$

- Coefficients stored, compressed, into "relightable image files" and visualized interactively (RTI viewer)
- Widely used estimation pipeline (RTI builder)

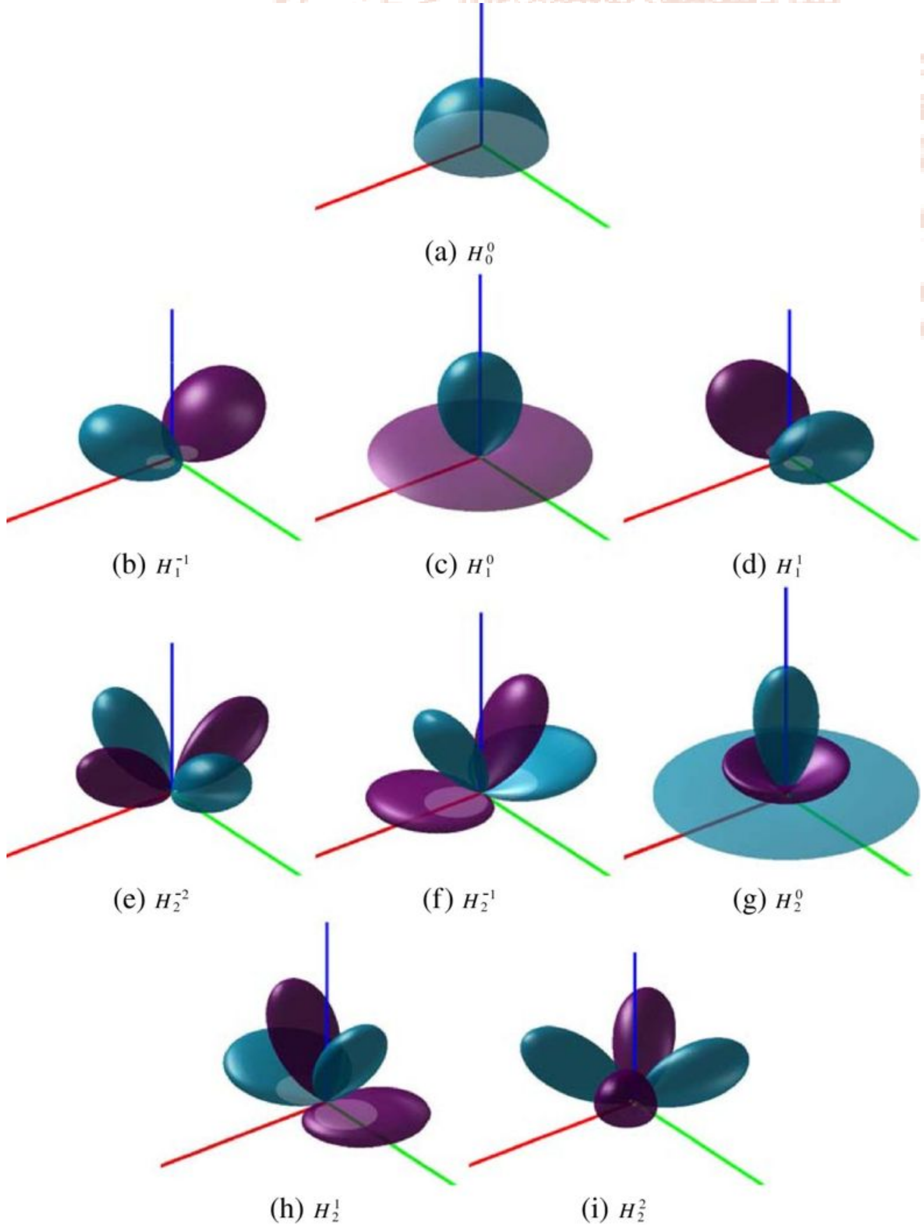






HEMISPHERICAL HARMONICS

- PTM almost completely destroy the specular component and any high frequency behavior
- Better solutions?
  - Higher order polynomials,
  - Hemispherical Harmonics (Gautron 2004) alternative set of basis functions on the unit sphere that are particularly aimed at non-negative function values.
  - Functions typically expressed in terms of Θ,Φ elevation and azimuth



HEMISPHERICAL HARMONICS

$$H_i = H_l^m;\ i = \left(\left(l+1\right)l - m\right) + 1;\ \text{Order} = \left(l+1\right):$$

Order 1:

$$H_1\left(\theta,\phi\right) = 1/\sqrt{\left(2\pi\right)}$$

Order 2:

$$H_2\left(\theta,\phi\right) = \sqrt{\left(6/\pi\right)}\left(\cos\left(\phi\right)\sqrt{\left(\cos\left(\theta\right) - \cos\left(\theta\right)^2\right)}\right)$$

$$H_3\left(\theta,\phi\right) = \sqrt{\left(3/\left(2\pi\right)\right)}\left(-1 + 2\cos\left(\theta\right)\right)$$

$$H_4\left(\theta,\phi\right) = \sqrt{\left(6/\pi\right)}\left(\sin\left(\phi\right)\sqrt{\left(\cos\left(\theta\right) - \cos\left(\theta\right)^2\right)}\right)$$

Order 3:

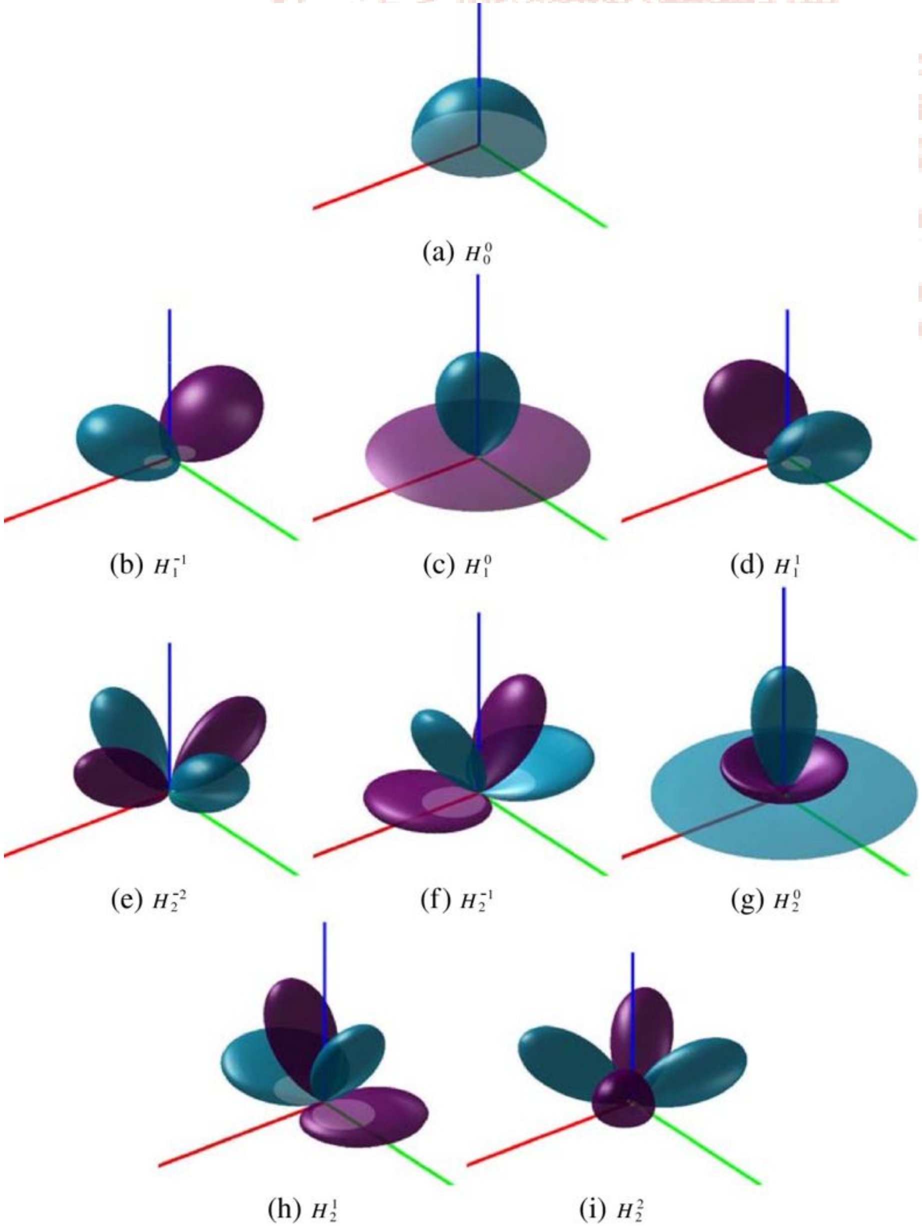
$$H_5\left(\theta,\phi\right) = \sqrt{\left(30/\pi\right)}\left(\cos\left(2\phi\right)\left(-\cos\left(\theta\right) + \cos\left(\theta\right)^2\right)\right)$$

$$H_6\left(\theta,\phi\right) = \sqrt{\left(30/\pi\right)}\left(\cos\left(\phi\right)\left(-1 + 2\cos\left(\theta\right)\right)\sqrt{\left(\cos\left(\theta\right) - \cos\left(\theta\right)^2\right)}\right)$$

$$H_7\left(\theta,\phi\right) = \sqrt{\left(5/\left(2\pi\right)\right)}\left(1 - 6\cos\left(\theta\right) + 6\cos\left(\theta\right)^2\right)$$

$$H_8\left(\theta,\phi\right) = \sqrt{\left(30/\pi\right)}\left(\sin\left(\phi\right)\left(-1 + 2\cos\left(\theta\right)\right)\sqrt{\left(\cos\left(\theta\right) - \cos\left(\theta\right)^2\right)}\right)$$

$$H_9\left(\theta,\phi\right) = \sqrt{\left(30/\pi\right)}\left(\left(-\cos\left(\theta\right) + \cos\left(\theta\right)^2\right)\sin\left(2\phi\right)\right)$$



(a) H_0^0 (b) H_1^{-1} (c) H_1^0 (d) H_1^1 (e) H_2^{-2} (f) H_2^{-1} (g) H_2^0 (h) H_2^1 (i) H_2^2

HEMISPHERICAL HARMONICS

Order 4:

$$H_{10}\left(\theta,\phi\right) = 2\sqrt{(35/\pi)}\cos\left(3\phi\right)\left(\cos(\theta) - \cos(\theta)^2\right)^{3/2}$$

$$H_{11}(\theta,\phi) = \sqrt{(210/\pi)}\cos(2\phi)\left(-1 + 2\cos(\theta)\right)\left(-\cos(\theta) + \cos(\theta)^2\right)$$

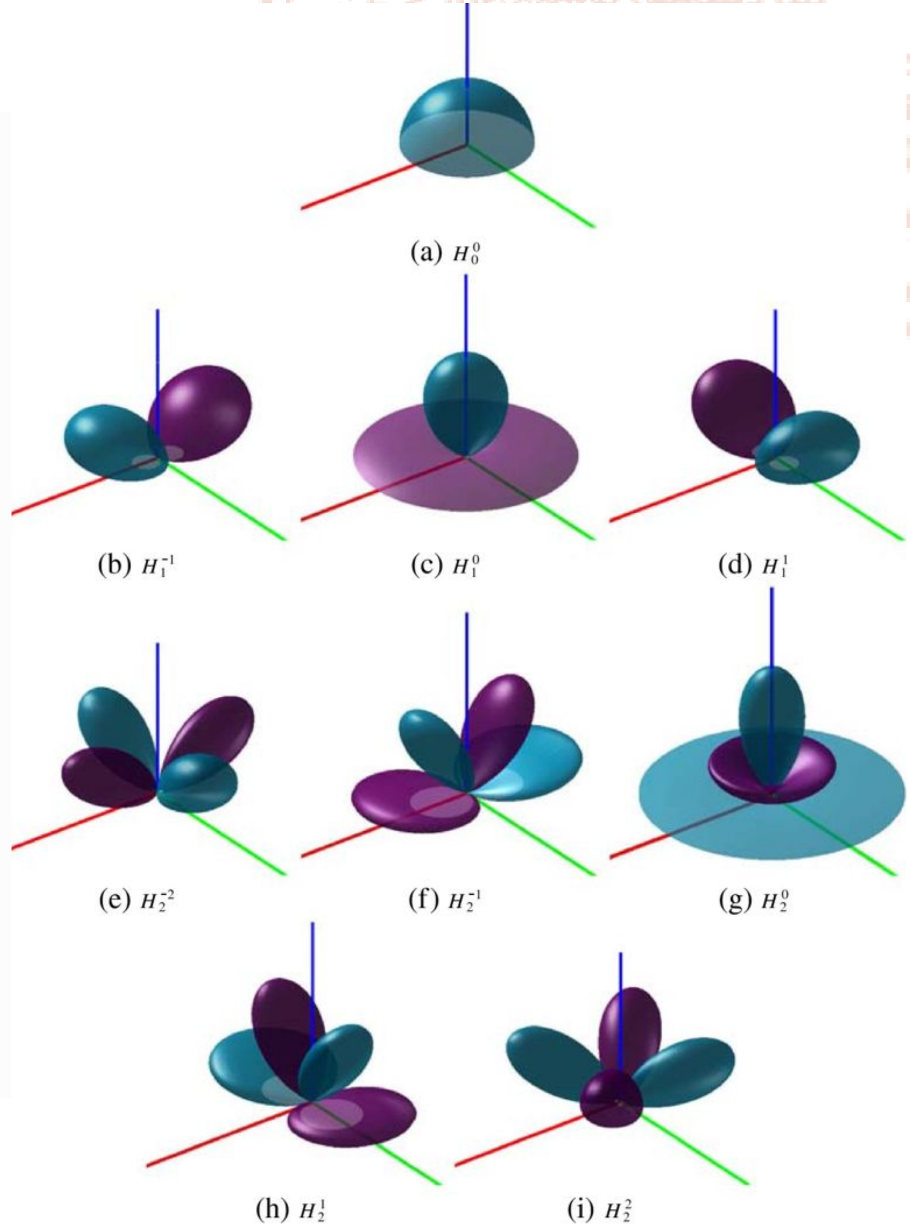
$$H_{12}(\theta,\phi) = 2\sqrt{(21/\pi)}\cos(\phi)\sqrt{(\cos(\theta) - \cos(\theta)^2)}\left(1 - 5\cos(\theta) + 5\cos(\theta)^2\right)$$

$$H_{13}(\theta,\phi) = \sqrt{(7/(2\pi))}\left(-1 + 12\cos(\theta) - 30\cos(\theta)^2 + 20\cos(\theta)^3\right)$$

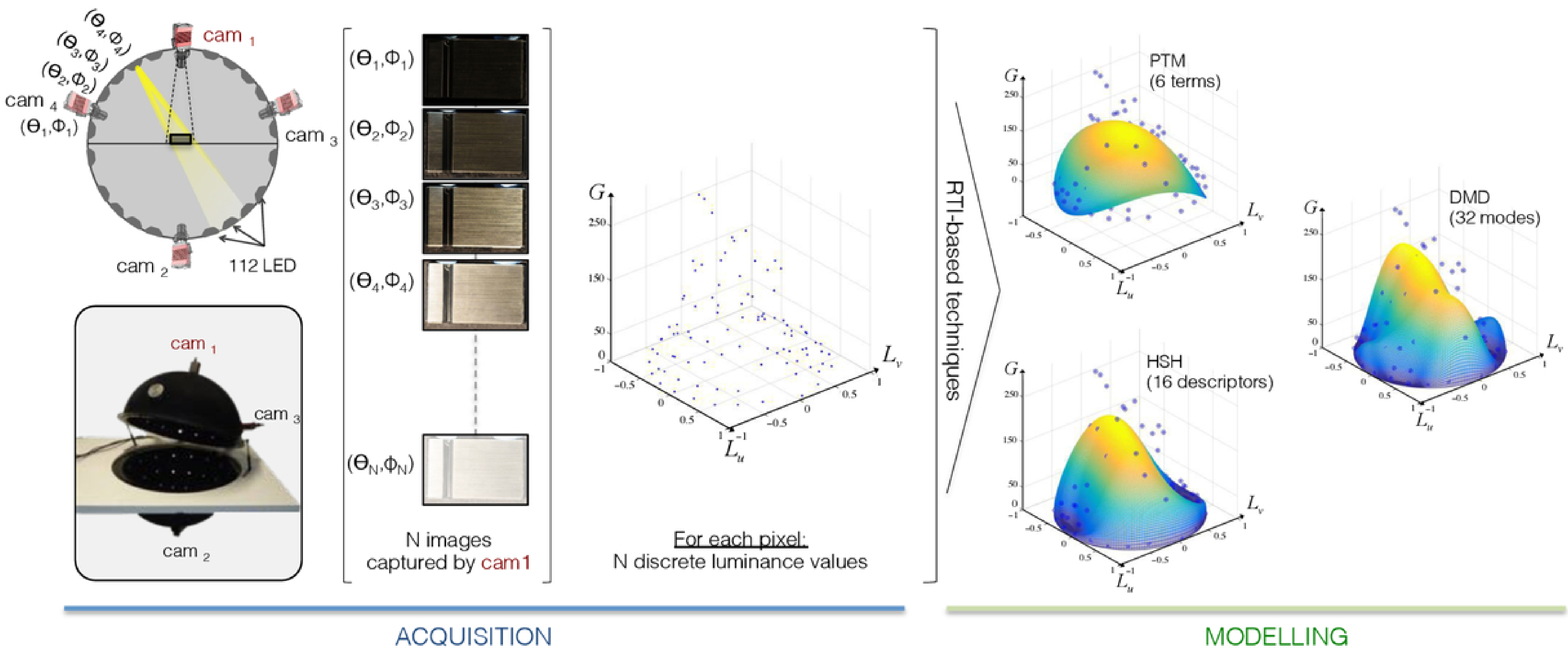
$$H_{14}(\theta,\phi) = 2\sqrt{(21/\pi)}\sin(\phi)\sqrt{(\cos(\theta) - \cos(\theta)^2)}\left(1 - 5\cos(\theta) + 5\cos(\theta)^2\right)$$

$$H_{15}(\theta,\phi) = \sqrt{(210/\pi)}\left(-1 + 2\cos(\theta)\right)\left(-\cos(\theta) + \cos(\theta)^2\right)\sin(2\phi)$$

$$H_{16}\left(\theta,\phi\right) = 2\sqrt{(35/\pi)}\sin\left(3\phi\right)\left(\cos(\theta) - \cos(\theta)^2\right)^{3/2}$$



FITTING FUNCTIONS



- From G. Pitard

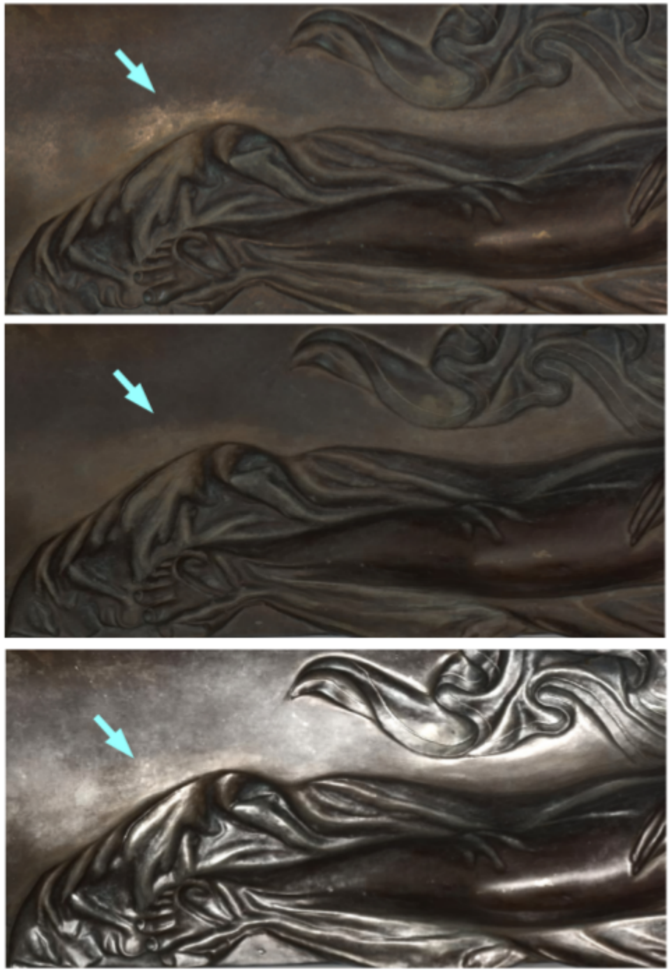
Pitard, G., Le Goïc, G., Mansouri, A. et al. Discrete Modal Decomposition: a new approach for the reflectance modeling and rendering of real surfaces Machine Vision and Applications (2017) 28: 607

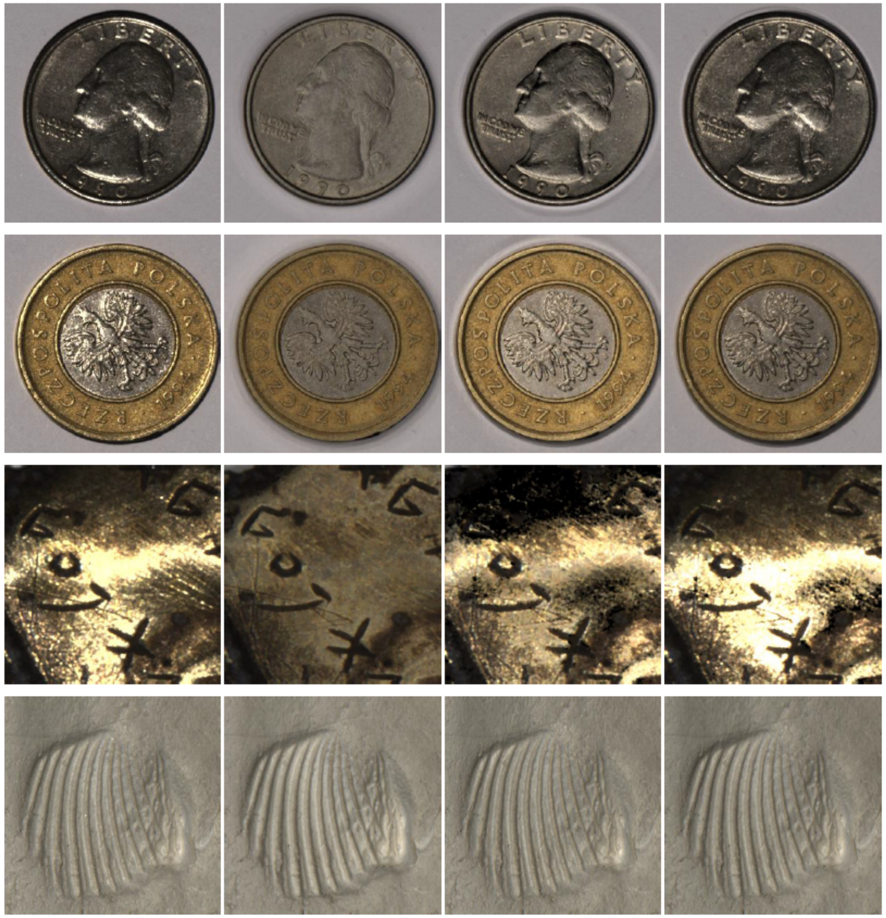
RELIGHTING

- Storing the PTM/HSH coefficients per pixel, we can create relightable images, and given light direction components, or elevation and azimuth, we can directly estimate pixel color
- Common simplification: store coefficients only for luminance and store constant per pixel chromaticity
- Quite popular in Cultural Heritage, but
  - Only 2 order PTM (6 coefficients) 3-rarely 4 order HSH (9 or 16 coefficients), with poor/no calibration
  - Poor behavior for specular materials
  - Best function? Unclear: depends on data...

RELIGHTING QUALITY?

- Are we seeing real details?





BEST FUNCTION?

- Pitard et al. 2017

Pitard, G., Le Goïc, G., Mansouri, A. et al. Discrete Modal Decomposition: a new approach for the reflectance modeling and rendering of real surfaces Machine Vision and Applications (2017) 28: 607

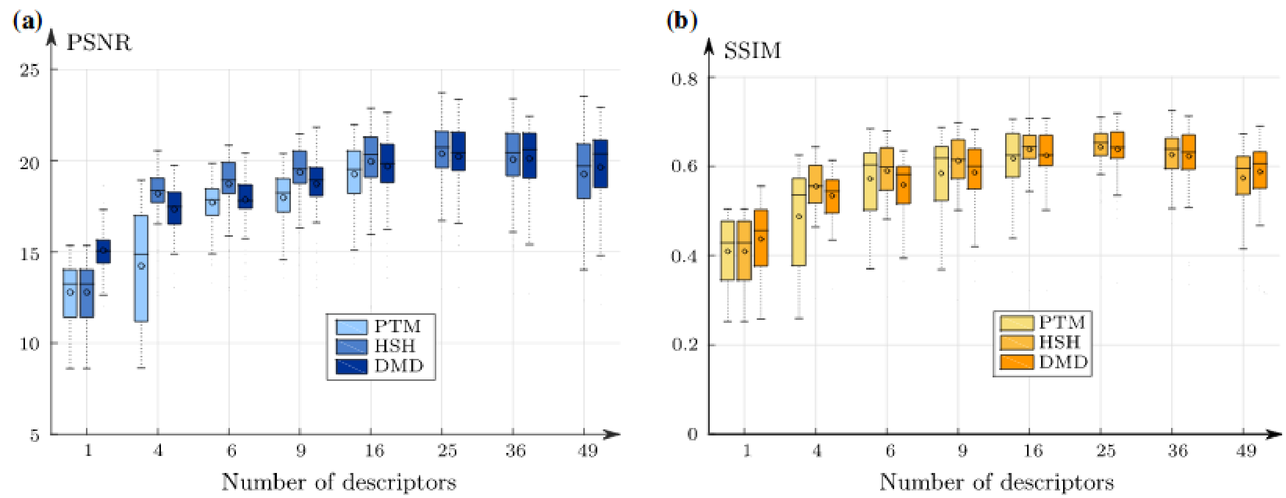
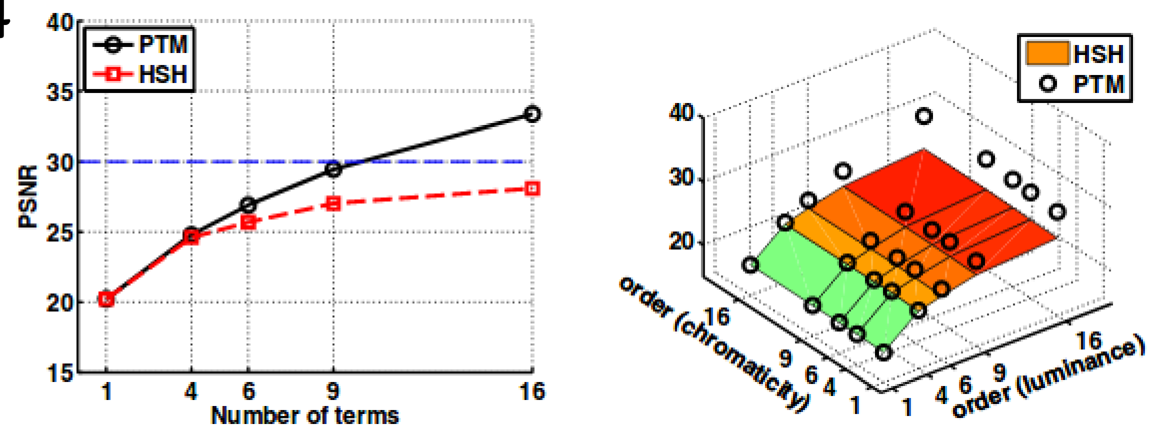


Fig. 13 Comparison of RTI quality based on **a** PSNR and **b** SSIM values, versus the number of descriptors used for reconstruction, for *Dataset 1*

- Zhang & Drew 2014

Zhang, Mingjing, and Mark S. Drew. "Efficient robust image interpolation and surface properties using polynomial texture mapping." EURASIP Journal on Image and Video Processing 2014.1 (2014): 25

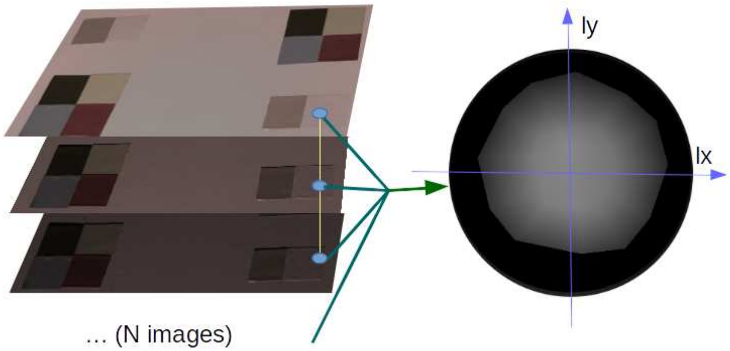


(a) (b)

DIRECT RELIGHTING

- Interpolation of appearance profile to get arbitrary relighting
- Simple method: Radial Basis Functions
  - Local interpolation may avoid effects of “distant” light directions, shadows or highlights
  - Without simplifications, not suitable for online interactive relighting

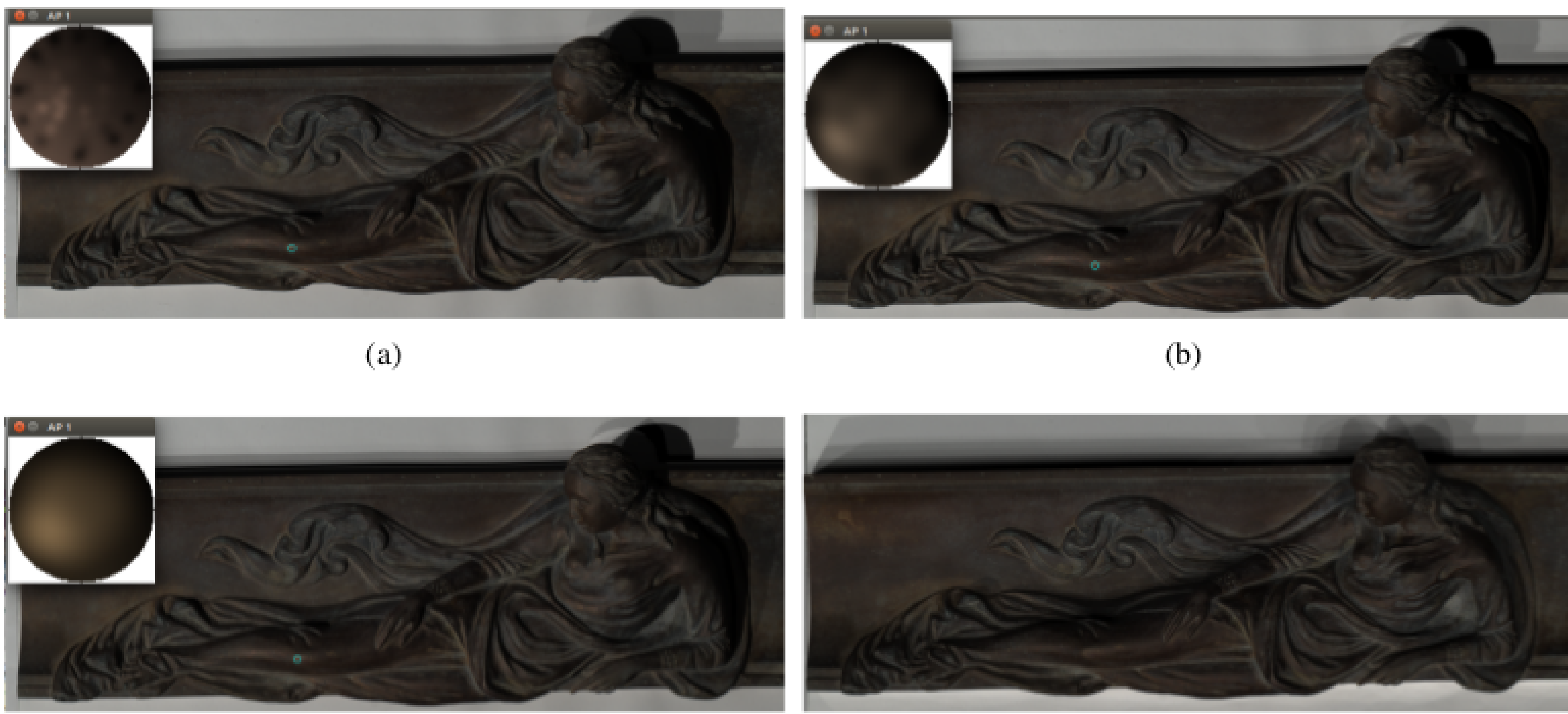
$$I(\vec{l}) = \sum_{i=1}^{N} \alpha_i e^{\frac{||\vec{l}-\vec{l}_i||^2}{R^2}}$$



Giachetti, A., Ciortan, I., Daffara, C., Pintus, R., & Gobbetti, E. "Multispectral RTI analysis of heterogeneous artworks." proc. GCH 2017 (2017).

DIRECT RELIGHTING

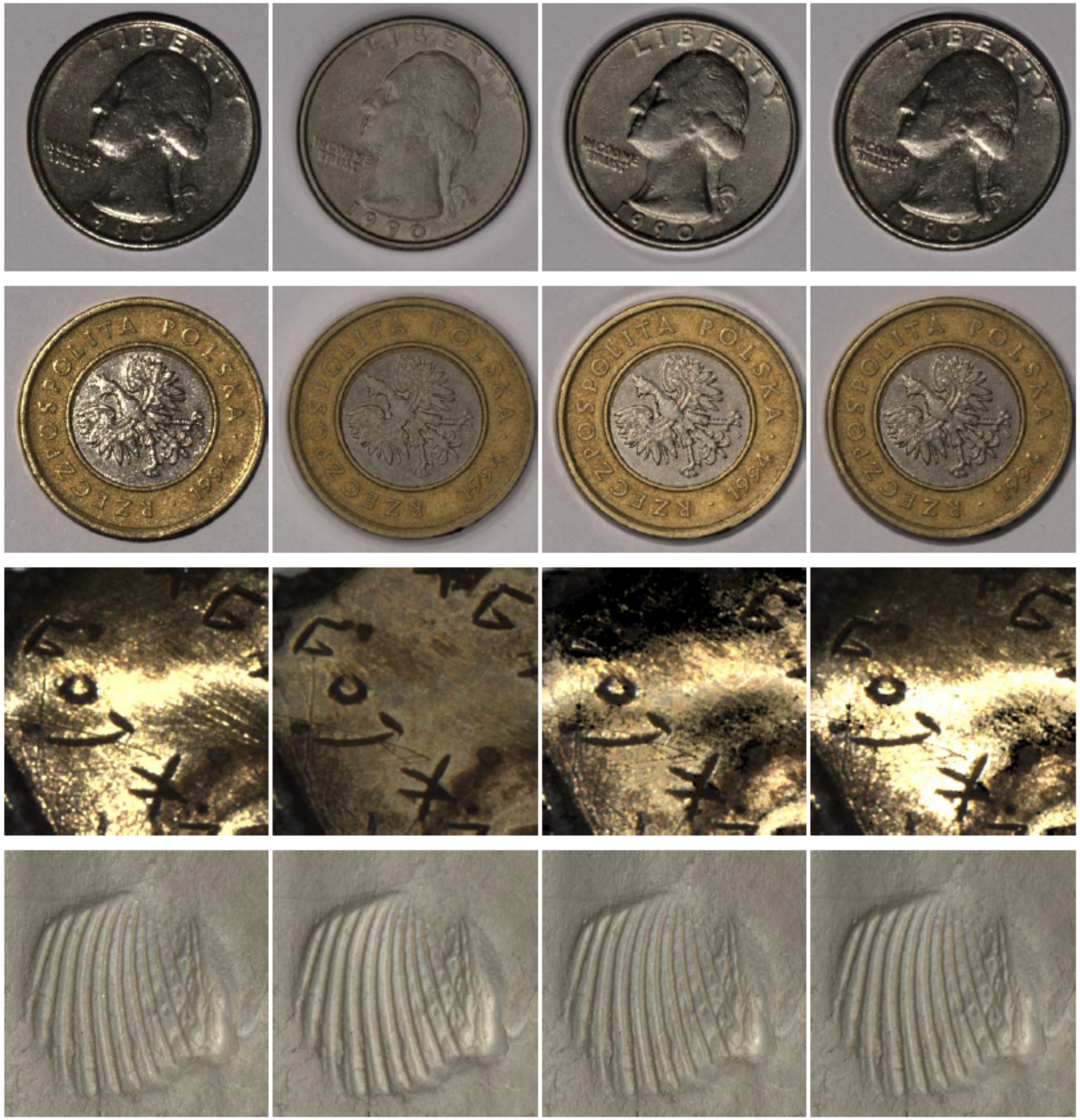
- (a)(b)(c): Direct relightigting with R=0.1,0.3,0.6 of a MLIC capture of a bronze statue. (d) PTM relighting



(a) (b) (c) (d)

QUALITY EVALUATION

- Improved relighting quality both according to objective and subjective measurements
- Relighting quality may depend on materials and perceived quality may depend on user tasks



Pintus, Dulecha, Jaspe Villanueva, Giachetti, Ciortan, Gobbetti
Objective and Subjective Evaluation of Virtual Relighting from Reflectance Transformation Imaging Data Proc. GCH 2018

DIRECT VISUALIZATION

- Improved relighting quality both according to objective and subjective measurements
- Relighting quality may depend on materials and perceived quality may depend on user tasks (GCH 2018)
- Leave one out relighting compared with original images on a set of about 50 images
  - Similarity measured with PSNR or SSIM

Method	PSNR															
	Coin1				Coin2				Lamina				Shell			
	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.
PTM	20.96	22.37	17.14	25.56	22.43	23.71	19.85	25.60	20.27	19.67	16.03	24.26	24.53	24.78	21.77	27.50
HSH	22.92	23.01	21.37	26.1	23.67	24.00	22.07	26.11	21.26	20.99	16.63	25.44	**26.60**	**26.68**	**24.41**	29.51
RBF	**23.74**	**24.83**	**21.99**	**27.22**	**24.35**	**25.01**	**22.37**	**26.96**	**22.45**	**21.01**	**16.88**	**27.90**	25.48	24.23	21.61	**29.82**

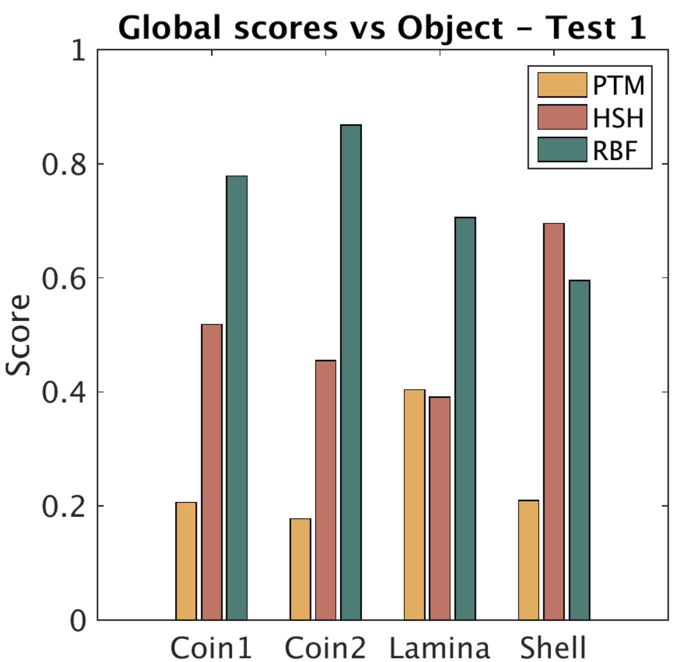
Method	SSIM															
	Coin1				Coin2				Lamina				Shell			
	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.	Avg.	Med.	1st Qr	3rd Qr.
PTM	0.61	0.64	0.49	0.68	0.70	0.73	0.65	0.75	0.61	0.59	0.50	0.71	0.81	0.83	0.75	0.89
HSH	0.66	0.68	0.61	0.75	0.75	0.76	0.71	0.80	0.61	0.64	0.53	0.72	**0.85**	**0.87**	**0.82**	0.91
RBF	**0.77**	**0.82**	**0.70**	**0.87**	**0.81**	**0.84**	**0.76**	**0.88**	**0.78**	**0.80**	**0.72**	**0.88**	0.81	0.83	0.72	**0.93**

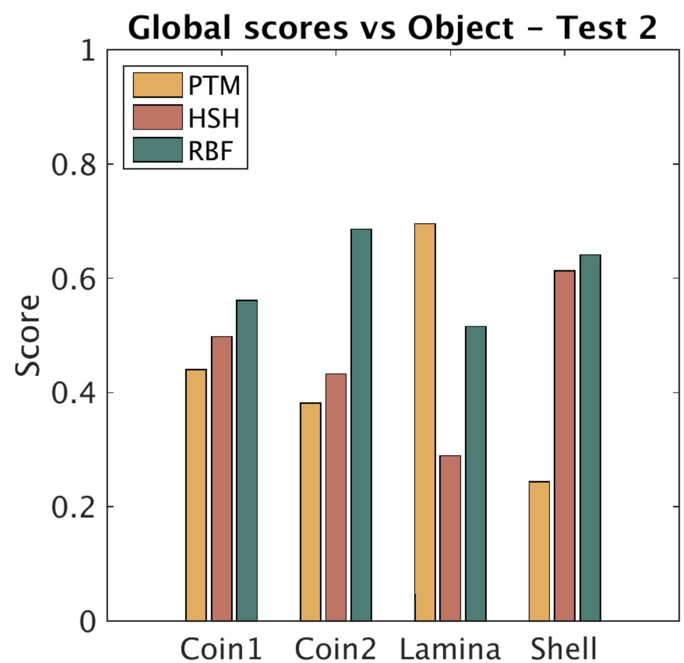
USER DIFFERENCES

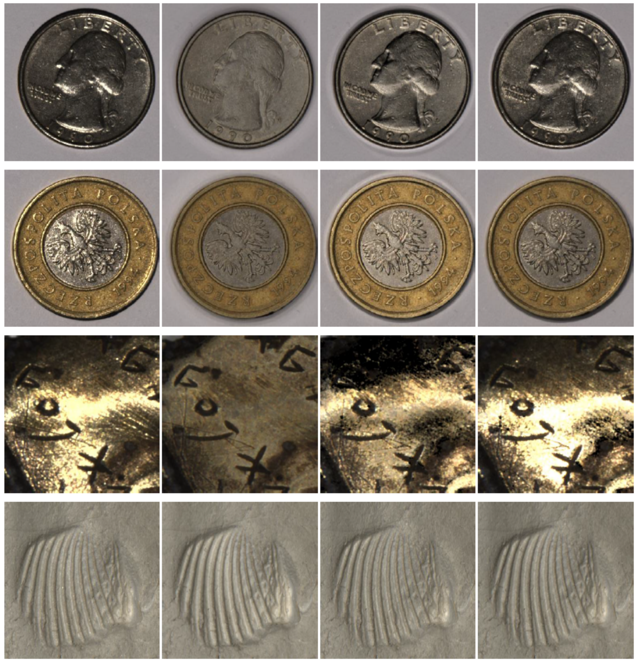
- Two tests: similarity to reference image and no-reference quality perception
- Cultural Heritage experts in some cases prefer PTM in no-reference comparison for the matte appearance

MATERIAL DIFFERENCES

- Preferred relighting method depends also on material/object
- In extremely specular object a "matte" rendering can be preferred







Compressed RBF Relighting

- Ponchio et al. 2018
  - Compress AP info using PCA

$$\rho(x,y,l) = \sum_{i=1}^{N} \rho_i(x,y) \exp\left(\frac{\|l - l_i\|_2^2}{\sigma^2}\right) = \sum_{i=1}^{N} \rho_i(x,y)\phi_i(l)$$

$$p(x,y) \simeq \mu + \sum_{j=1}^{M} a_k(x,y) B_k$$

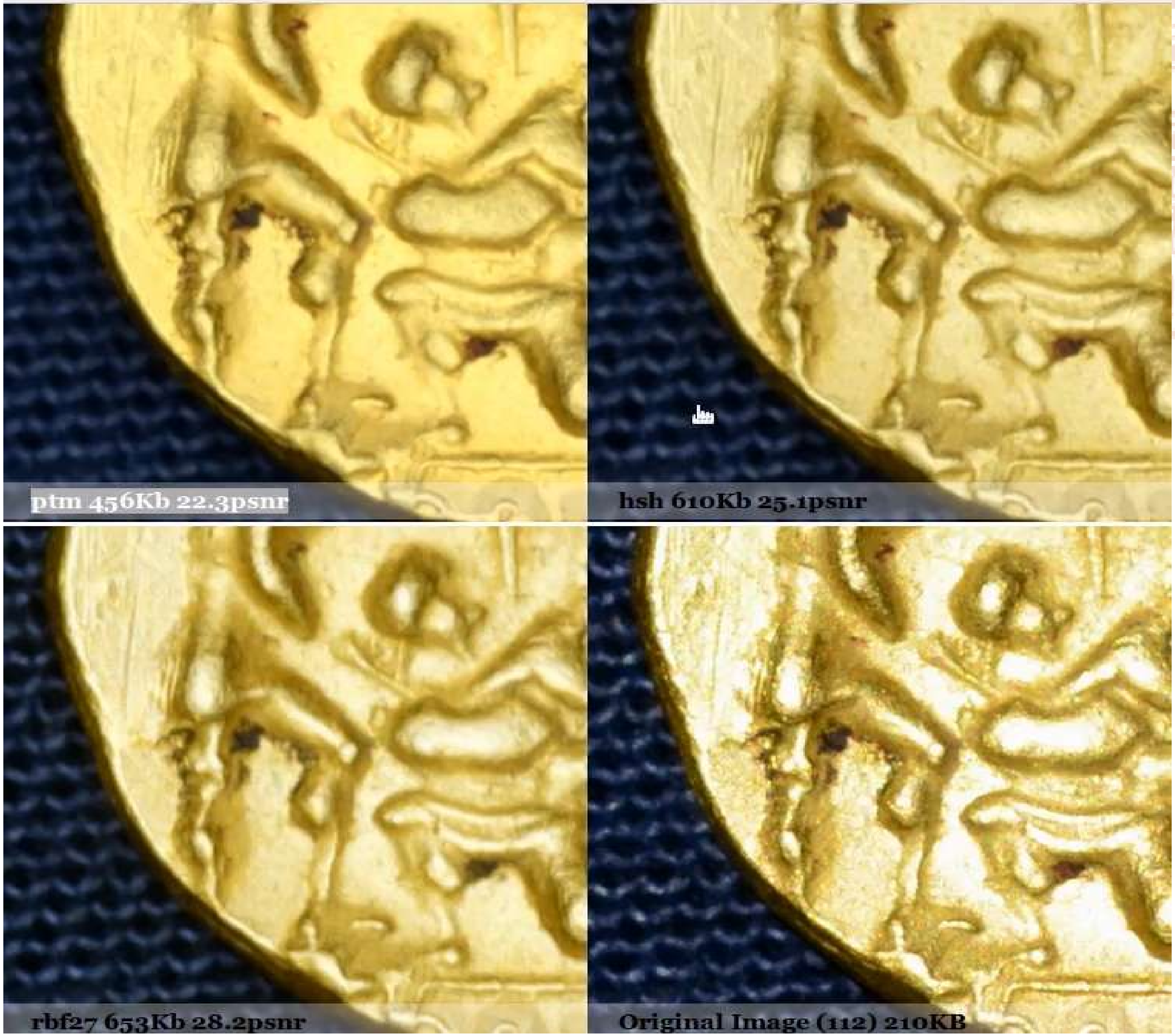
$$\begin{aligned} \rho(x,y,l) &\simeq \sum_{i=1}^{N} \phi_i(l) \left(\mu_i + \sum_{k=1}^{M} a_{i,k}(x,y) B_{i,k}\right) \\ &\simeq \sum_{i=1}^{N} \phi_i(l)\mu_i + \sum_{k=1}^{M} a_{i,k}(x,y) \sum_{i=1}^{N} \phi_i(l) B_{i,k} \end{aligned}$$

$$\rho(x,y,l) = w_0(l) + \sum_{k=1}^{M} a_k(x,y) w_k(l)$$

$$\begin{aligned} w_0(l) &= \sum_{i=1}^{N} \phi_i(l)\mu_i \\ w_k(l) &= \sum_{i=1}^{N} \phi_i(l) B_{i,k} \end{aligned}$$

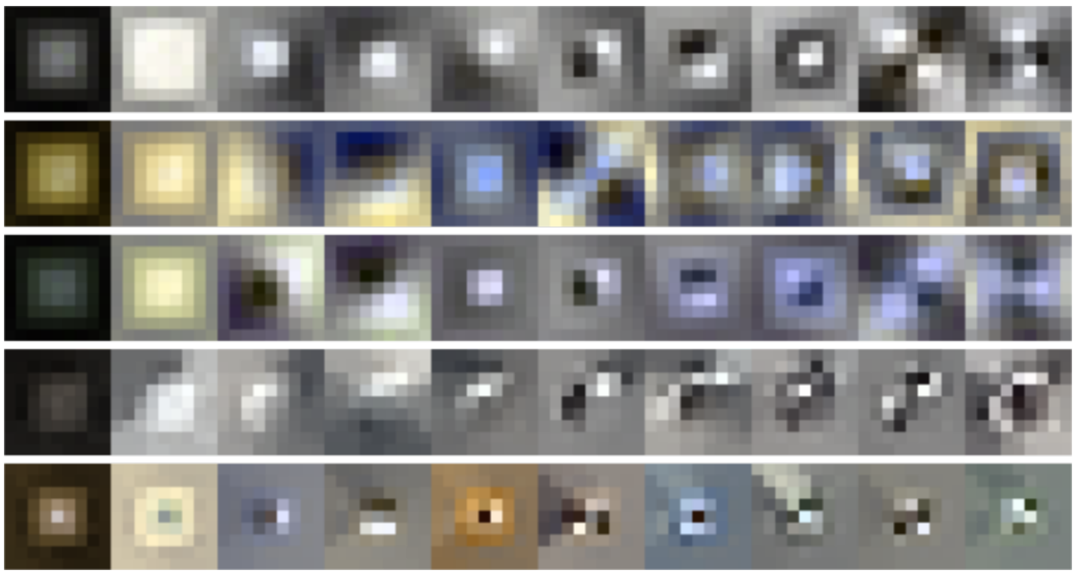
COMPRESSED RBF VS PTM ONLINE RELIGHT

COMPRESSION ISSUES



NOTES

- Weights can be precomputed if we assume that light directions are constant across the image
- Another idea proposed in the paper is to resample input light direction in a fixed set, and use bilinear interpolation
- We can also compare the basis obtained from different datasets in the resampled direction space



RELIGHT QUALITY VS SIZE

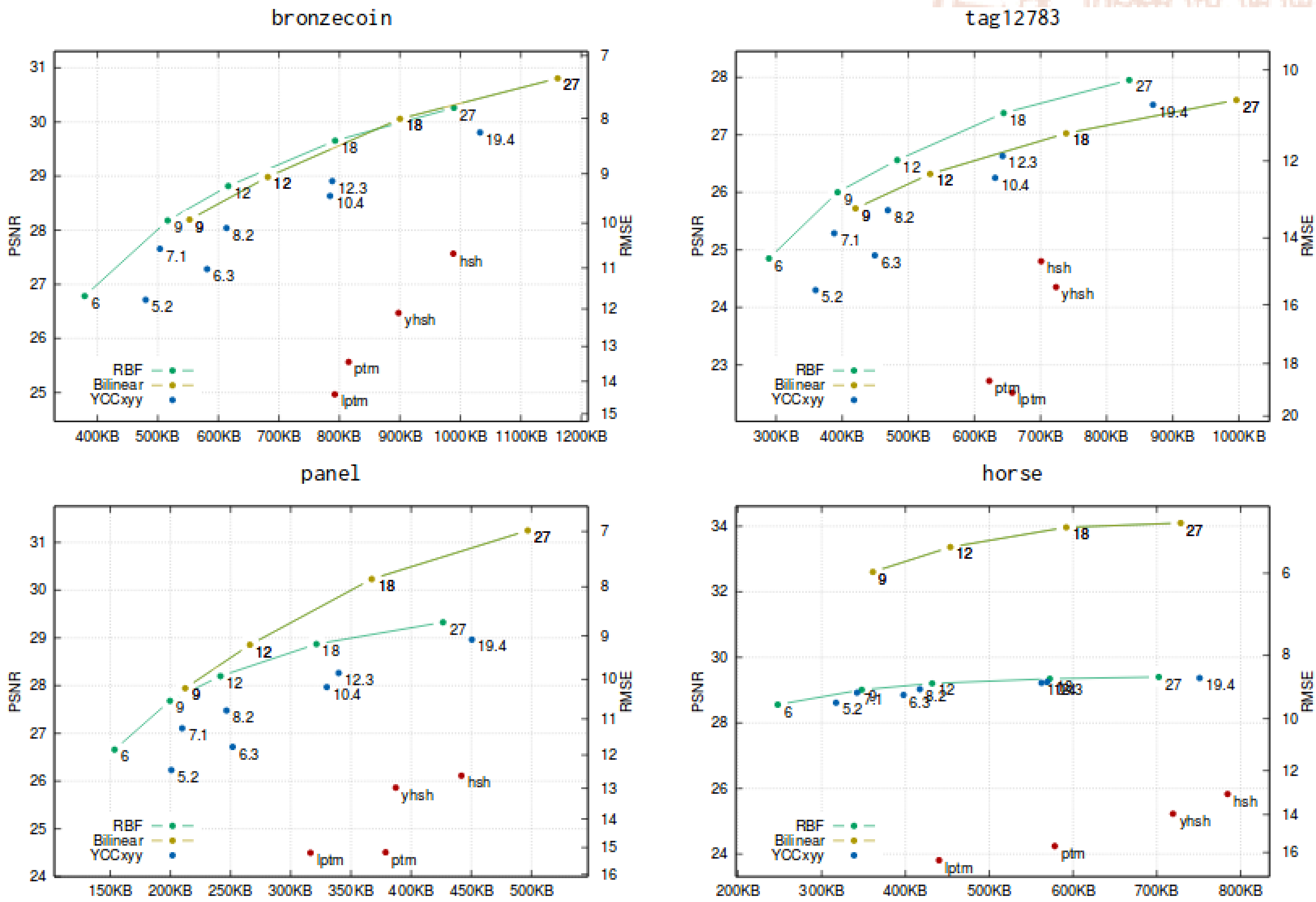


Figure 3: Image quality (PSNR,RMSE) vs size (kB) for different representations and different datasets. For the YCC methods the number X.Y reported in the graphs, indicate the number of luminance and chroma coefficients, respectively.

PHOTOMETRIC STEREO

- Coefficients of fitted functions can be linked to surface normals, assuming links between the functions and reflectance models (BRDF slices)
- This is commonly used for the 3D reconstruction method called Photometric Stereo
- Classic fitting funtion/reflectance model is simply Lambertian, assuming parallel projection

$$L_k(i,j) = a\,\vec{l_k}(i,j)\cdot\vec{n}_k(i,j)$$

- Classically soved via Least Squares given the MLIC with N images
- Materials are not actually Lambertian
- We could use more complex BRDF functions
  - More parameters, more images needed for the solution
  - But there are many practical problems

Better model or better fit?

- More complex parametric models tested in the literature
  - Es. Isotropic Ward model (Goldman 2004)
  - Improvements on benchmarks, but may not be large on real images
- Light direction sampling is sparse
  - Light sources distances in lx,ly space are large compared with the wavelength of specular effects
- And accuracy of light direction estimation poor
  - We have seen this in the acquisition notes
- And the view direction is far from being parallel
  - And there are a lot of outliers also for "accurate" local reflectance models
    - Global illumination: shadows, interreflections
  - Ideally we should write functions including the pixelwise view direction, calibrating it over the image

Robust Photometric Stereo

- These sources of error make reflectance estimate from images quite hard (and not actually solved)
- But for Photometric Stereo we can adopt a different solution:
  - Consider a simple reflectance model (e.g. Lambertian), fitting well the real behavior in most of the light directions' space
  - Discard "outliers" from the parameters estimation at each pixel location
  - This is the most popular/effective solution
  - But how to select inliers/discard outliers?
    - Robust fitting methods
      - Trimmed fit (remove high/low intensity values)
      - Low-Rank Matrix Completion and Recovery (Wu et al 2010)
      - Least Median of Squares (Drew et al. 2012)
    - Increased computational complexity

Least Median of Squares

- Ensures up to 50% breakdown point (half input measurements can be outliers)
- Proved to be capable to provide excellent results for Photometric Stereo and RTI fitting

Standard Least Median of Squares
Input:
- AP: appearance profile
- ε: fraction of outliers
- P: probability of picking at least an inlier subset

Output: Solution S
begin
  Compute number of trials $nTrials(\varepsilon, P)$
  do
    sAP_p = Random sampling of an AP's subset of p cardinality
    Compute fitting coefficients from sAP_p
    Compute fitting coefficients from elements with the best half residuals (Refinement)
    Evaluate the median residual $M_J = \underset{i}{med}\ r_i^2$
    Update solution S if M_J is less than current minimal residual
  while $J < nTrials$
  Compute inliers for S with $r_i^2 \leq (2.5\sigma)^2$
  Compute final fit S using all the inliers
  return S

SPEEDING UP ROBUST ESTIMATION

- Exploiting spatial coherence (Pintus 2017)

Input:
- *APARRAY*: nxm 2D-array of appearance profiles
- M: number of sparse seed pixels

Output: nxm 2D-array of fitting coefficients

begin
Compute similarity map of I
Select a sparse set of M seed pixels S
for *pixel* $p \in S$ **do in parallel**
Compute fitting coefficients with $th_p = 0$ and uniform weights
Compute the residual threshold $th = \underset{p}{avg}\,(r_p + 2.5\sigma_p)^2$
do
Select candidate pixel set C
for *pixel* $c \in C$ **do in parallel**
Compute fitting coefficients with $th_c = th$ and weights from the most similar, already processed, neighbor of c
while C *is not empty*;
return nxm 2D-array of fitting coefficients

Pintus R, Giachetti A, Pintore G, Gobbetti E. Guided Robust Matte-Model Fitting for Accelerating Multi-light Reflectance Processing Techniques. BMVC 2017

SPEEDING UP ROBUST ESTIMATION

- Results
  - Relevant speedup of the estimation
  - Quality preserved
  - OK for PTM evaluation

Dataset	Time	# Solve	Avg.	Med.	1st Qr	3rd Qr.	Speed-up
Ball	2.8s/0.2s	2.5M/122K	2.0/2.1	2.1/2.1	1.5/1.6	2.6/2.6	~14x
Cat	8.3s/0.5s	7.2M/345K	6.4/6.7	5.7/5.9	3.7/3.8	7.9/8.6	~16x
Pot1	10.2s/0.7s	9.2M/481K	7.4/8.0	5.3/6.0	3.2/3.4	8.9/10.1	~14x
Bear	7.7s/0.7s	6.6M/463K	5.3/5.5	4.2/4.4	2.5/2.6	6.7/7.0	~10x
Pot2	5.9s/0.8s	5.6M/547K	11.8/12.7	9.6/10.7	5.5/5.6	16.4/18.7	~7x
Buddha	8.3s/0.7s	7.1M/449K	9.0/9.4	7.3/7.7	4.5/4.6	10.9/12.0	~11x
Goblet	4.7s/0.6s	4.2M/357K	12.9/14.3	11.2/11.9	6.8/7.1	16.7/20.0	~8x
Reading	4.5s/0.7s	4.4M/461K	12.8/13.3	7.2/7.4	4.2/4.3	14.7/16.1	~7x
Cow	4.4s/1.1s	4.2M/721K	21.3/24.0	21.9/26.1	13.2/14.9	29.2/33.4	~4x
Harvest	9.3s/2.6s	8.8M/1.9M	24.3/25.2	18.5/19.6	8.0/8.6	34.5/35.9	~4x

Guided Least Median of Squares

Input:

- AP: appearance profile
- wAP: appearance profile weights
- th: residual threshold
- ε: fraction of outliers
- P: probability of picking at least an inlier subset

Output: Solution S

begin

Compute number of trials $nTrials(\varepsilon, P)$

do

sAP_p = Weighted random sampling of an AP's subset of p cardinality

Compute fitting coefficients from sAP_p

Compute fitting coefficients from elements with the best half residuals (Refinement)

Evaluate the median residual $M_J = \underset{i}{med}\ r_i^2$

Update solution S if M_J is less than current minimal residual

while $(J < nTrials)$ or $(M_J < th)$

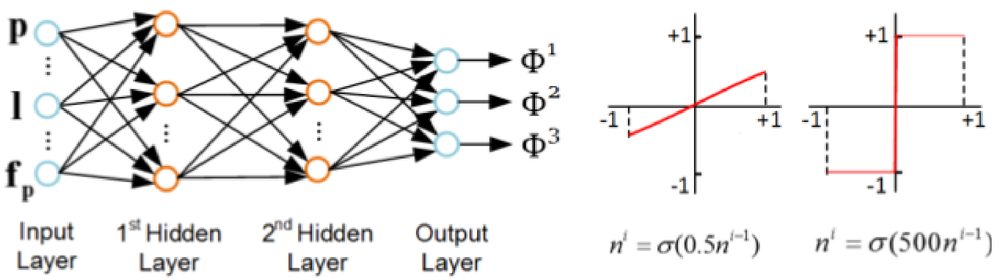
Compute inliers for S with $r_i^2 \leq (2.5\sigma)^2$

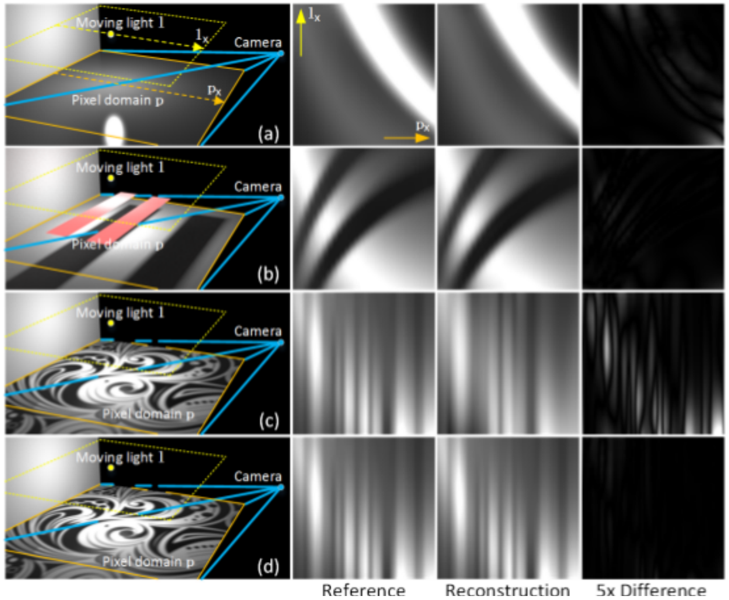
Compute final fit S using all the inliers

return S

Neural Networks?

- Yes: shallow networks instead of fitting functions
  - Ren et al. 2015
  - Light transport modelled assuming light source on a plane



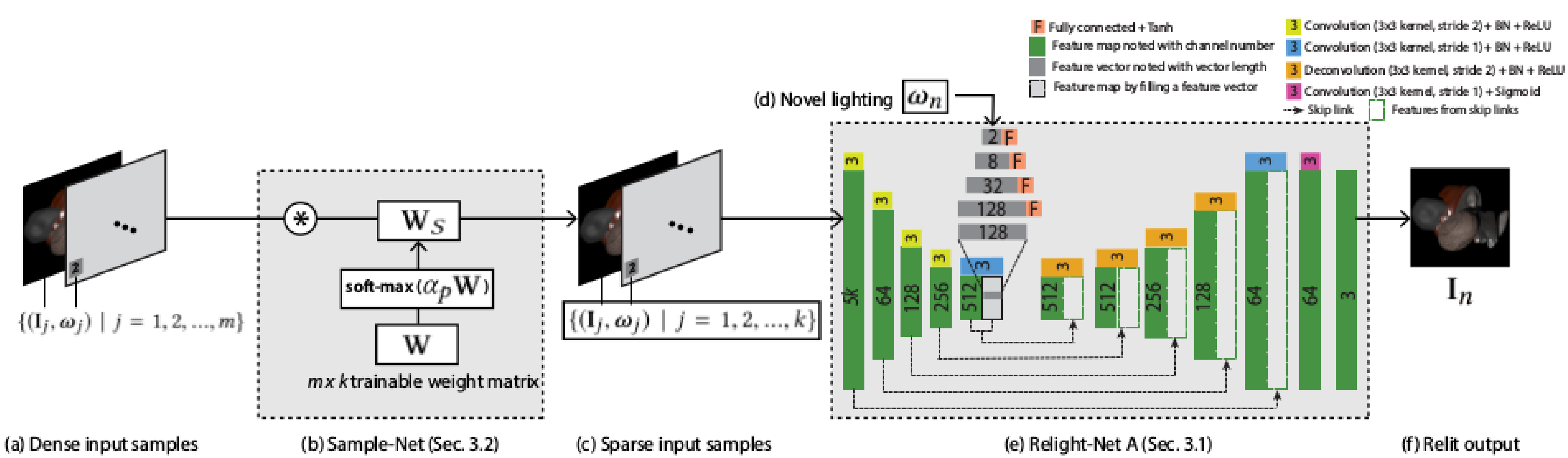


Peiran Ren, Yue Dong, Stephen Lin, Xin Tong, and Baining Guo. 2015. Image based relighting using neural networks. ACM Trans. Graph. 34, 4

- Or Convolutional Neural Networks..

NEURAL NETWORKS?

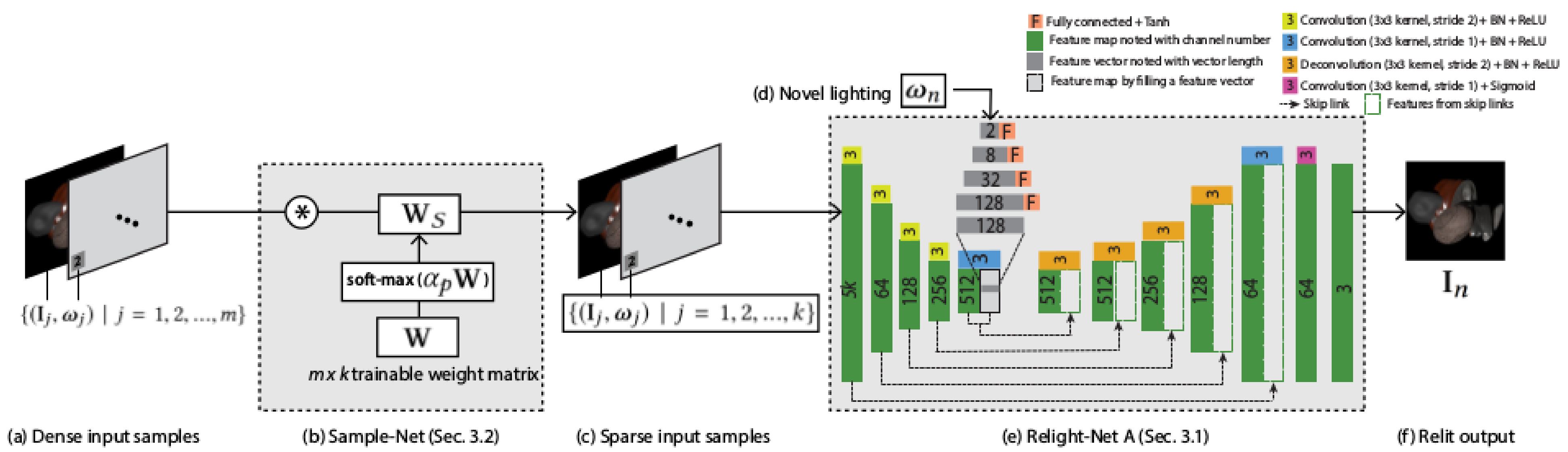
- Yes, CNN based relighting
  - Xu et al. 2018: RelightNet



Xu, Zexiang, et al. "Deep image-based relighting from optimal sparse samples." ACM Transactions on Graphics (TOG) 37.4 (2018)

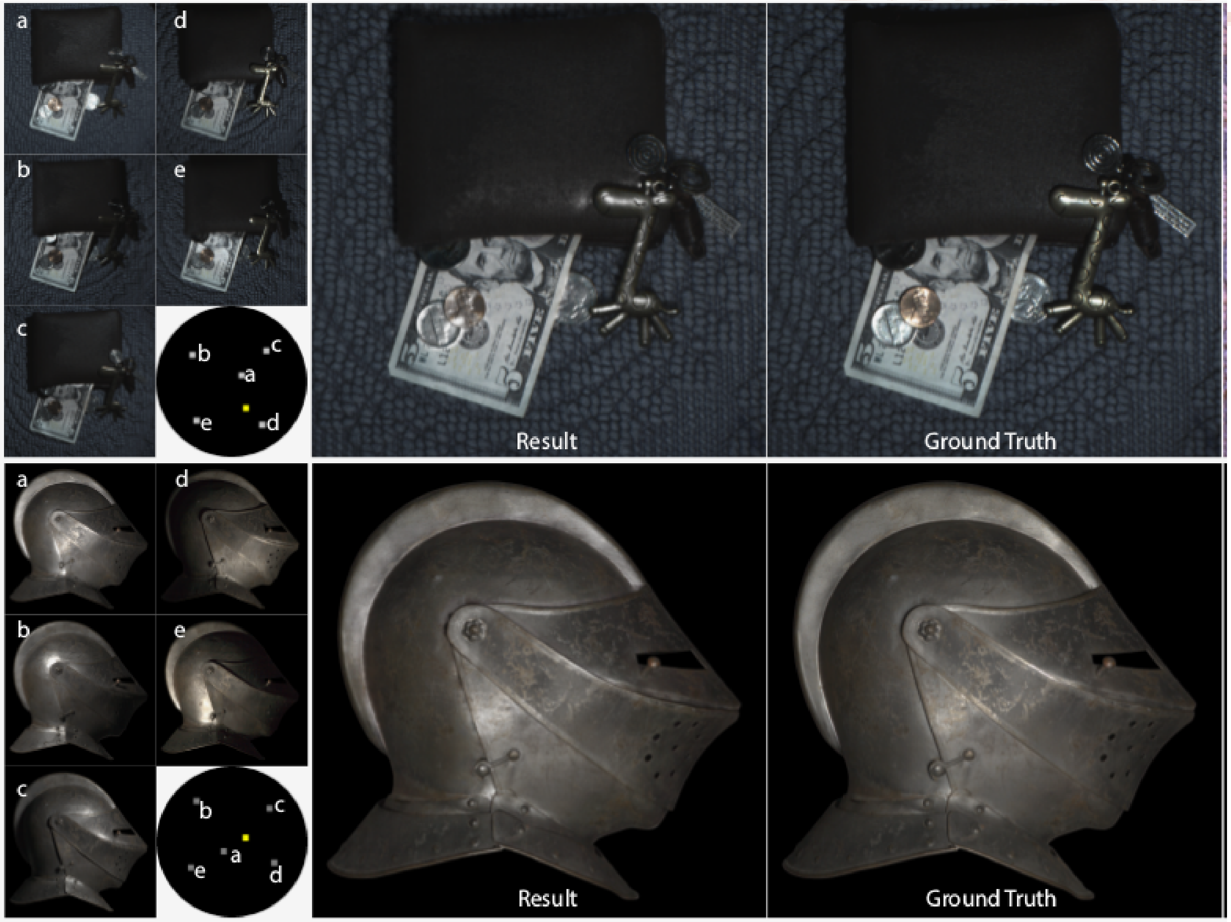
Relight Net (Xu et al. 2018)

- Fixed input light directions
- Two coupled networks
  - To learn relighting from sparse samples
  - To learn optimal sampling
  - Two different architectures proposed



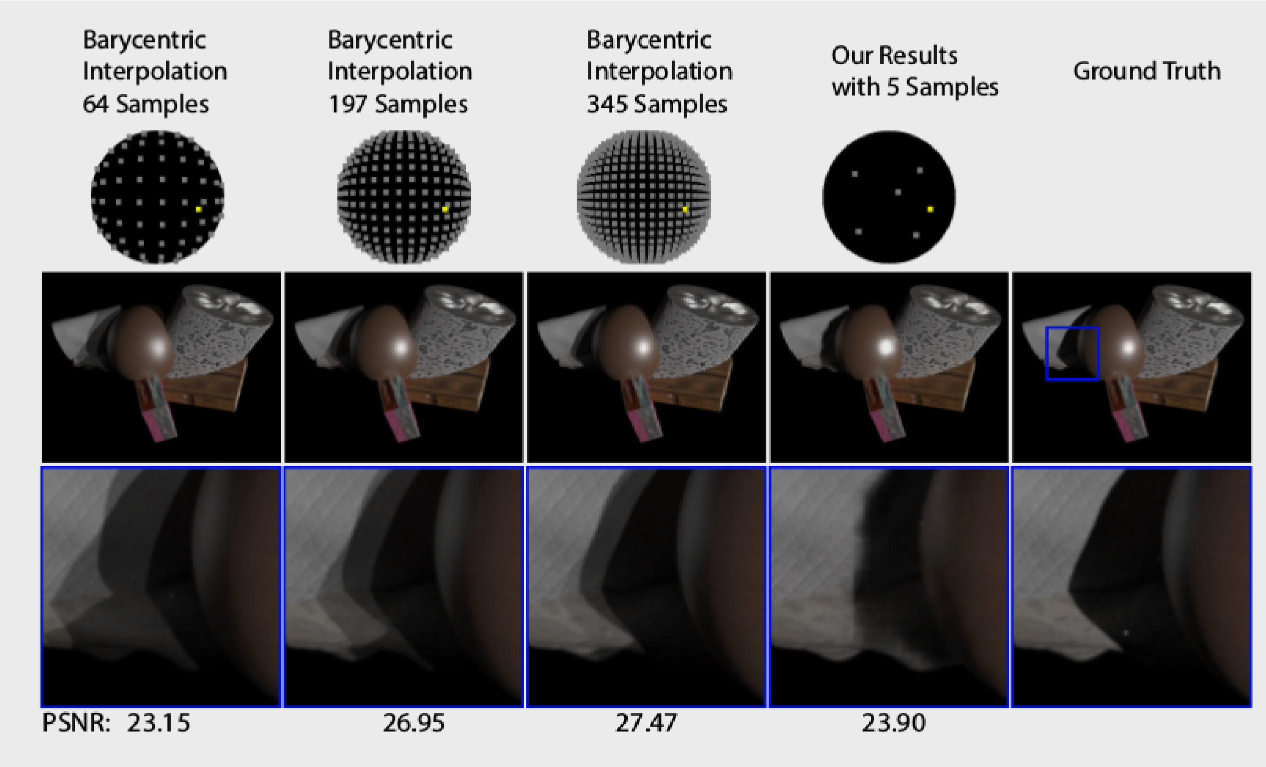
RELIGHTNET

- Impressive results
- Limitations
  - Directional lights
  - Fixed input



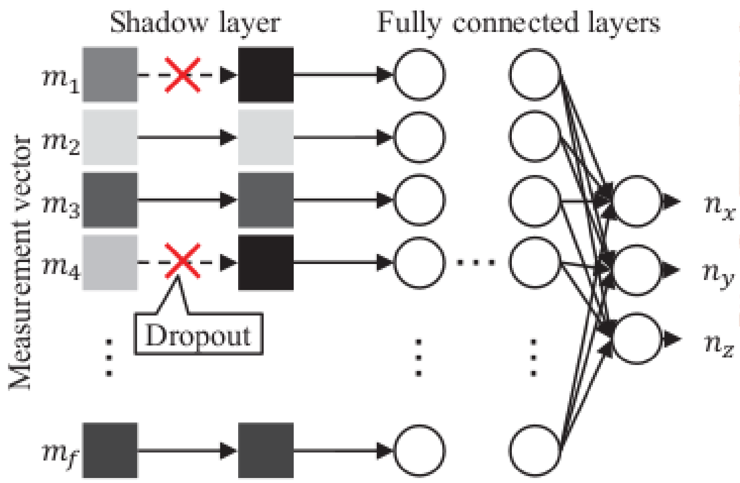
DIFFERENT BEHAVIOR

- From Xu et al. 2018
  - Comparison with direct interpolation
- Different kind of artifacts
  - But clearly artifacts



PHOTOMETRIC STEREO WITH NN

- Already proposed in the 90s
- Recent approach per pixel
  (Santo et al 2017)
- Per pixel prediction with shadow layer
  - Random dropout
  - Good results
  - Limitations (training/testing with same directional lights)



Layer	
1	Shadow Layer
2	Dense-(4096), ReLU, Dropout
3	Dense-(4096), ReLU, Dropout
4	Dense-(2048), ReLU, Dropout
5	Dense-(2048), ReLU, Dropout
6	Dense-(2048), ReLU, Dropout
7	Dense-(3)

Santo, H., Samejima, M., Sugano, Y., Shi, B., & Matsushita, Y. (2017, October). Deep photometric stereo network. ICCV 2017 pp. 501-509

Table 2. Comparison with benchmark [21].

	ball	cat	pot1	bear	buddha	cow	goblet	harvest	pot2	reading	AVG.
Proposed	3.44	7.21	7.90	7.20	13.30	8.49	12.35	**16.81**	8.80	17.47	10.30
Proposed W/ SL	2.02	6.54	7.05	6.31	12.68	8.01	11.28	16.86	**7.86**	15.51	**9.41**
ST14	**1.74**	**6.12**	**6.51**	6.12	10.60	13.93	10.09	25.44	8.78	**13.63**	10.30
IA14	3.34	6.74	6.64	7.11	**10.47**	13.05	**9.71**	25.95	8.77	14.19	10.60
WG10	2.06	6.73	7.18	6.50	10.91	25.89	15.70	30.01	13.12	15.39	13.35
AZ08	2.71	6.53	7.23	**5.96**	12.54	21.48	13.93	30.50	11.03	14.17	12.61
HM10	3.55	8.40	10.85	11.48	13.05	14.95	14.89	21.79	16.37	16.82	13.22
IW12	2.54	7.21	7.74	7.32	11.11	25.70	16.25	29.26	14.09	16.17	13.74
ST12	13.58	12.34	10.37	19.44	18.37	**7.62**	17.80	19.30	9.84	17.17	14.58
GC10	3.21	8.22	8.53	6.62	14.85	9.55	14.22	27.84	7.90	19.07	12.00
BASELINE	4.10	8.41	8.89	8.39	14.92	25.60	18.50	30.62	14.65	19.80	15.39

PS-FCN (CHEN ET AL 2018)

- Idea: siamese networks plus max pooling, then regression

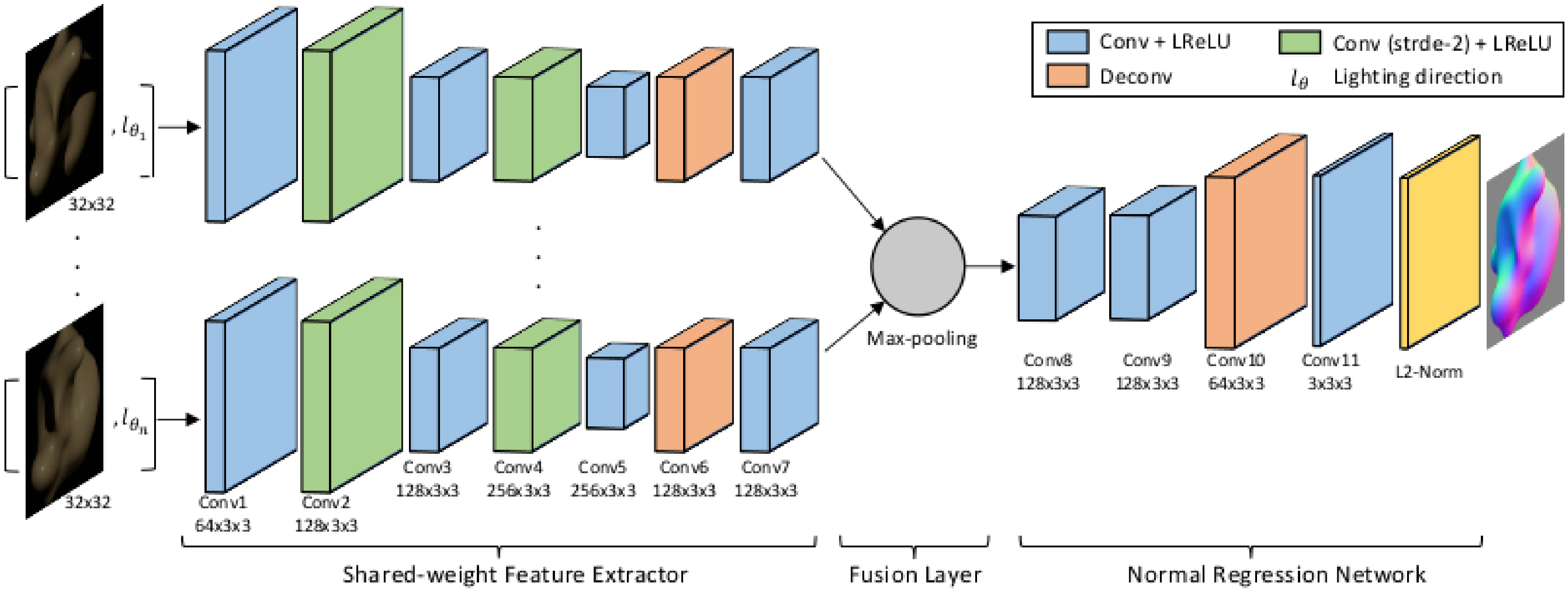


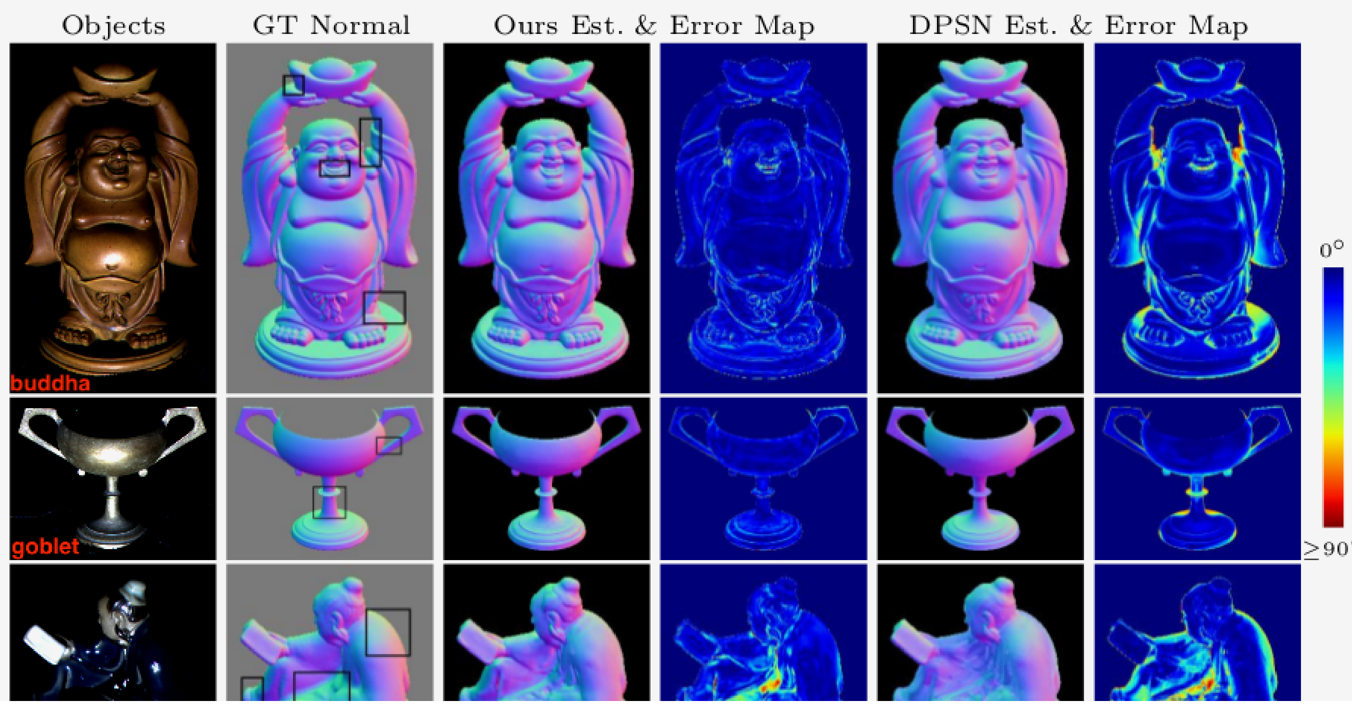
Fig. 3: Network architecture of PS-FCN.

Chen, Guanying, Kai Han, and Kwan-Yee K. Wong. "PS-FCN: A Flexible Learning Framework for Photometric Stereo." arXiv preprint arXiv:1807.08696 (2018).

PS-FCN (Chen et al 2018)

- Good results (but many methods provide similar ones, also robust fit)
- Good for uncalibrated PS

Method	ball	cat	pot1	bear	pot2	buddha	goblet	reading	cow	harvest	Avg.
L2 [1]	4.10	8.41	8.89	8.39	14.65	14.92	18.50	19.80	25.60	30.62	15.39
AZ08 [14]	2.71	6.53	7.23	**5.96**	11.03	12.54	13.93	14.17	21.48	30.50	12.61
WG10 [17]	2.06	6.73	7.18	6.50	13.12	10.91	15.70	15.39	25.89	30.01	13.35
IA14 [23]	3.34	6.74	6.64	7.11	8.77	10.47	9.71	14.19	13.05	25.95	10.60
ST14 [22]	**1.74**	**6.12**	**6.51**	6.12	8.78	10.60	10.09	13.63	13.93	25.44	10.30
DPSN [8]	2.02	6.54	7.05	6.31	7.86	12.68	11.28	15.51	8.01	16.86	9.41
PS-FCN (B+S+32, 16)	3.31	7.64	8.14	7.47	8.22	8.76	9.81	14.09	8.78	17.48	9.37
PS-FCN (B+S+32, 96)	2.82	6.16	7.13	7.55	**7.25**	**7.91**	**8.60**	**13.33**	**7.33**	**15.85**	**8.39**



ENHANCED RENDERING

- MLIC can be used not only for relighting, but also for enhanced rendering, e.g
- Improved edge detection
  - E.g. using fitting coefficients and gradient functions
  - Or simple differencing on few images
- Enhanced shading, eg. Fattal et al 2007
  - Few images, based on filtering and heuristics

Fattal, Raanan, Maneesh Agrawala, and Szymon Rusinkiewicz. "Multiscale shape and detail enhancement from multi-light image collections." ACM Transactions on Graphics (TOG). Vol. 26. No. 3. ACM, 2007

Input: 3 MLIC Images

Our Results: Enhanced Shape and Surface Detail

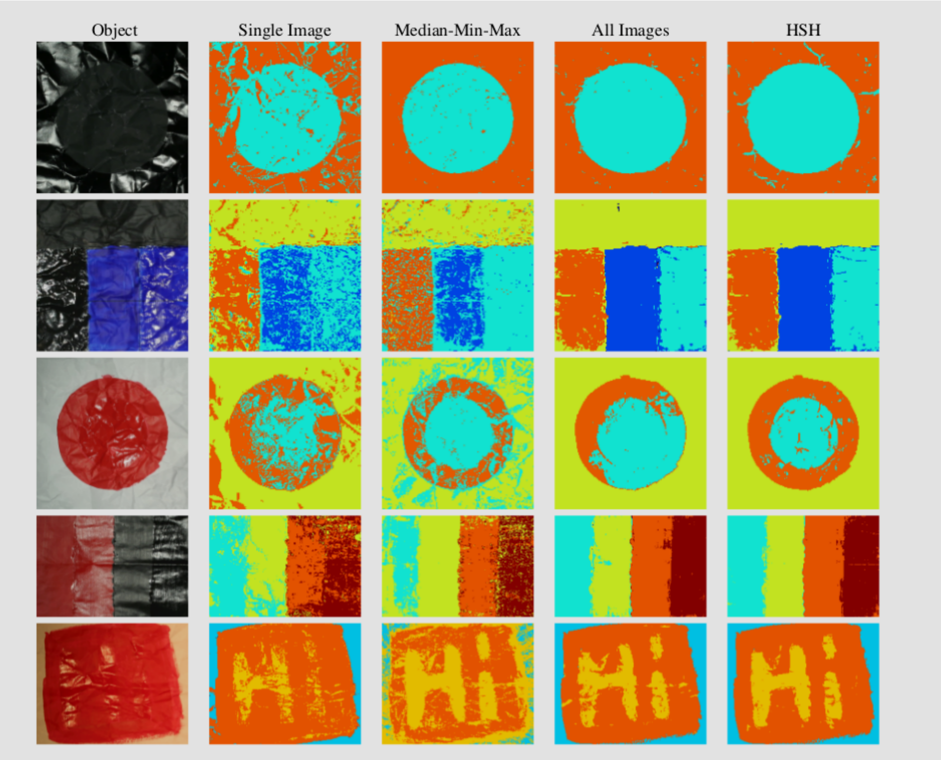
ENHANCED RENDERING

- Palma et al. for example proposed image enhancement methods using multiple image information to create a single enhanced image
  - es. Dynamic/static multilight enhancement

Gianpaolo Palma, Massimiliano Corsini, Paolo Cignoni, Roberto Scopigno, and Mark Mudge. 2010. Dynamic shading enhancement for reflectance transformation imaging. J. Comput. Cult. Herit. 3, 2

MATERIAL SEGMENTATION

- MLIC can be used also to analyze materials
- Knowing normals, BRDF estimation can be performed
- In general we can exploit the larger amount of information given by the multiple images to improve segmentation results, for example
    - e.g. Wang et al. 2009
    - Use of HSH coefficients as pixel descriptors
        - But with local normal info

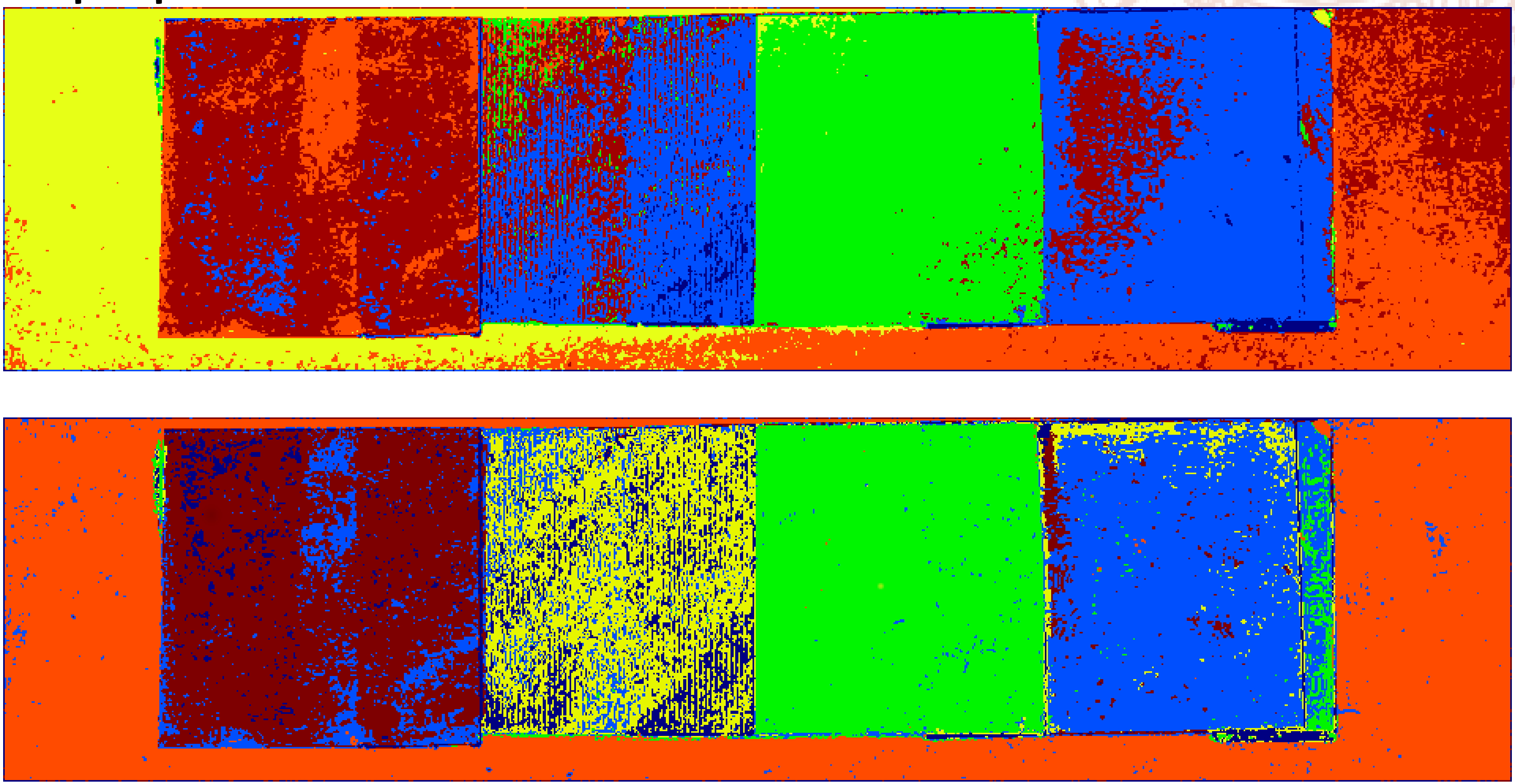


Wang, O., Gunawardane, P., Scher, S., & Davis, J. (2009). Material classification using BRDF slices.

CALIBRATION

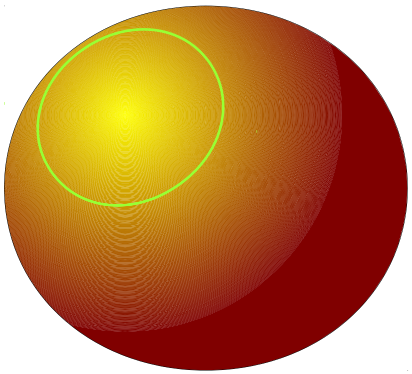
Giachetti, A., et al. "Light calibration and quality assessment methods for Reflectance Transformation Imaging applied to artworks' analysis." Optics for Arts, Architecture, and Archaeology V. Vol. 9527. International Society for Optics and Photonics, 2015.

- Quality of clustering based on coefficients is improved by proper calibration



SPECULARITY BASED FEATURES

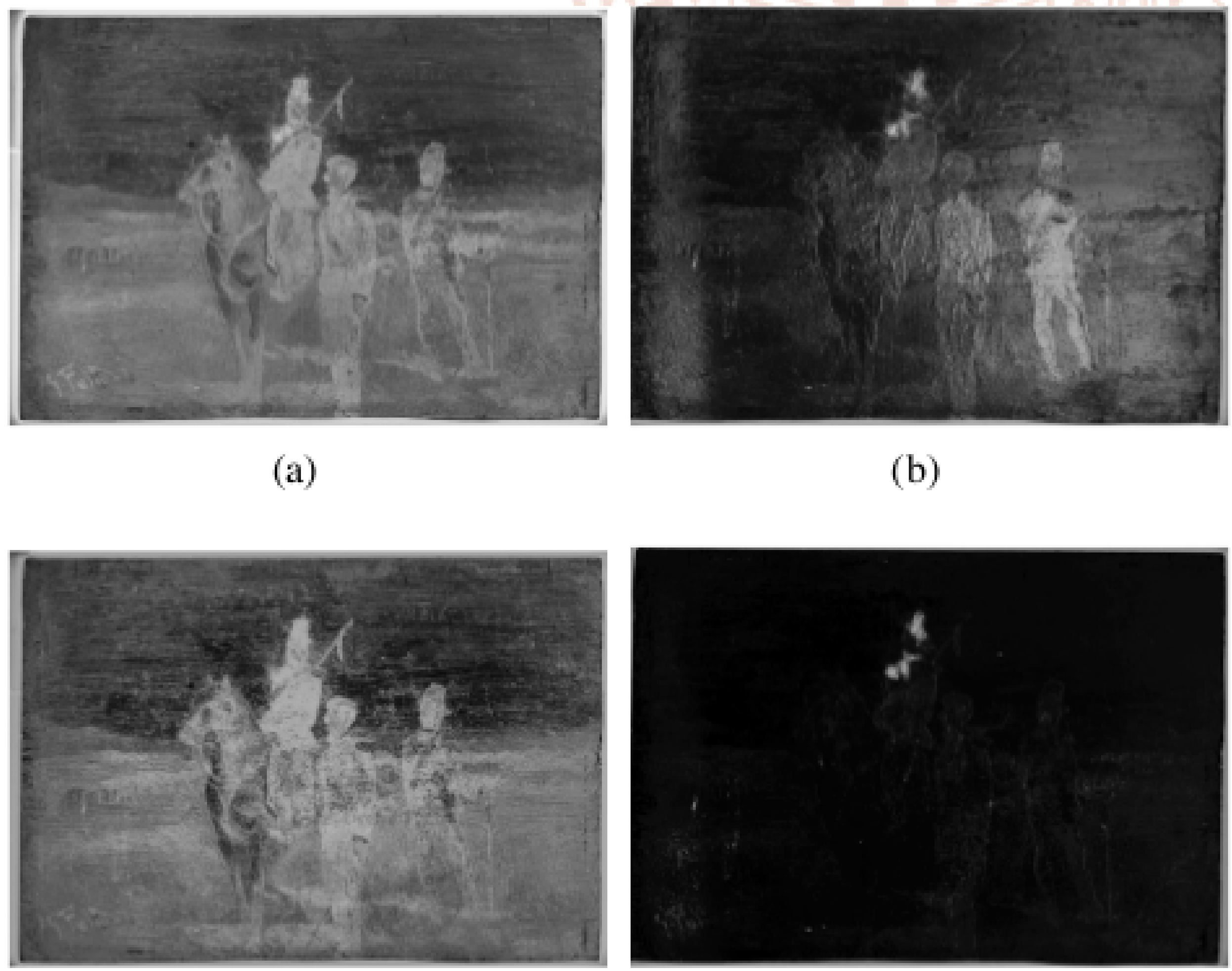
- Appearance profile array tools allow both direct visualization and model fitting (currently PS, PTM, modified PTM)
- We assume that fitted models represent the matte component of the material
- We could estimate local specularity dependent parameters to give useful visual hints. We computed
  - Integral of absolute deviations from PS/PTM models Lambertian Outliers map
  - Percentage of sampled directions where the deviations from model is above a threshold (Outlier directions map)
    - Approximately evaluating the specular intensity and width of the specular peak of the AP



Giachetti, A., Ciortan, I., Daffara, C., Pintus, R., & Gobbetti, E. "Multispectral RTI analysis of heterogeneous artworks." proc. GCH 2017 (2017).

SPECULARITY-DEPENDENT MAPS

- LD and OD Maps estimated on visible and IR acquisitions of the painting. A particular golden pigment is clearly distinguished
- Preliminary tests seem to suggest potential use of these features (multifrequency) for material segmentation



(a) (b)

WRAP UP

- MLIC can be acquired easily with low cost setups
  - Simple domes, light rings, handheld lights+cameras, or just two smartphones
- Several practical applications (excluding BRDF measurement) are based on them
  - Relightable images, enhanced rendering
  - Photometric stereo
  - Material segmentation
- **Image** acquisition **quality** and **calibration** are critical
  - But not sufficiently addressed in the literature
- Neural networks seem the future trend here too
  - but still not widely used in practical applications

USEFUL TOOLS

- CHI website
  - http://culturalheritageimaging.org/Technologies/RTI/
- Our tools:
  - http://www.andreagiachetti.it/rtitools
- Federico Ponchio's relight:
  - http://relight.duckdns.org/
- Scan4Reco project
  - http://www.scan4reco.eu/

QUESTIONS?