

Radiometric Calibration by Rank Minimization

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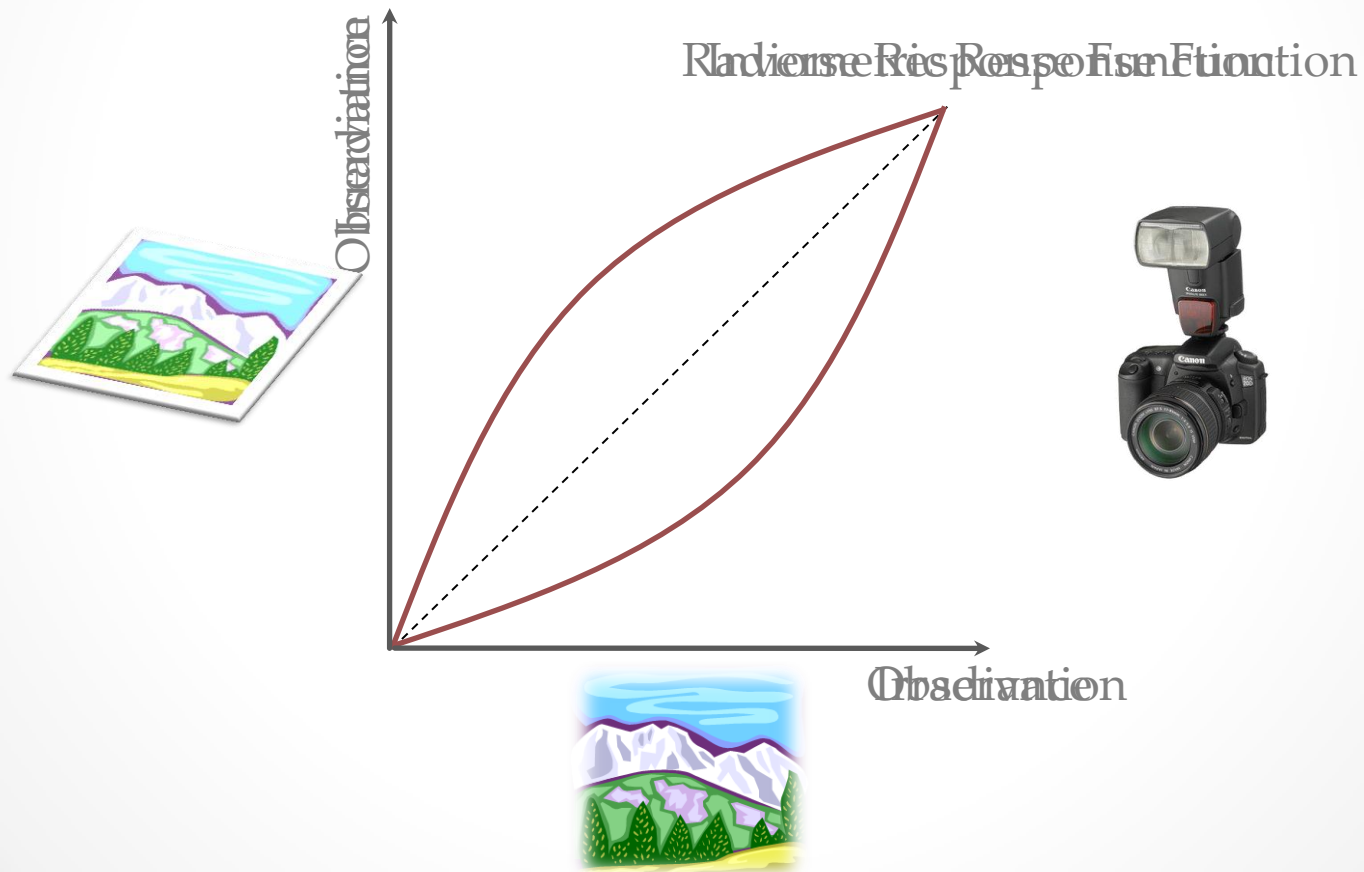
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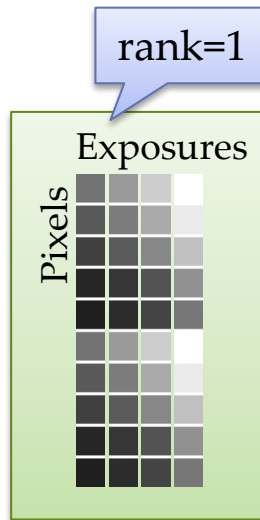
Radiometric calibration

Radiometric calibration

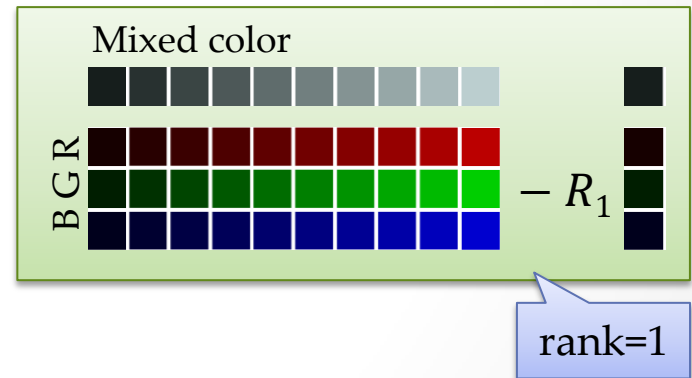
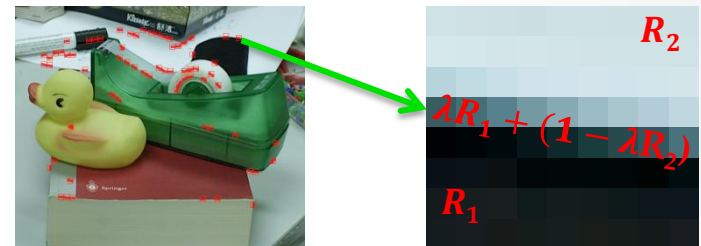


Low-rank structure of an irradiance matrix

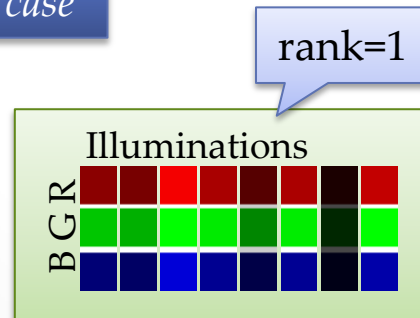
Multiple exposure case



Color mixture case

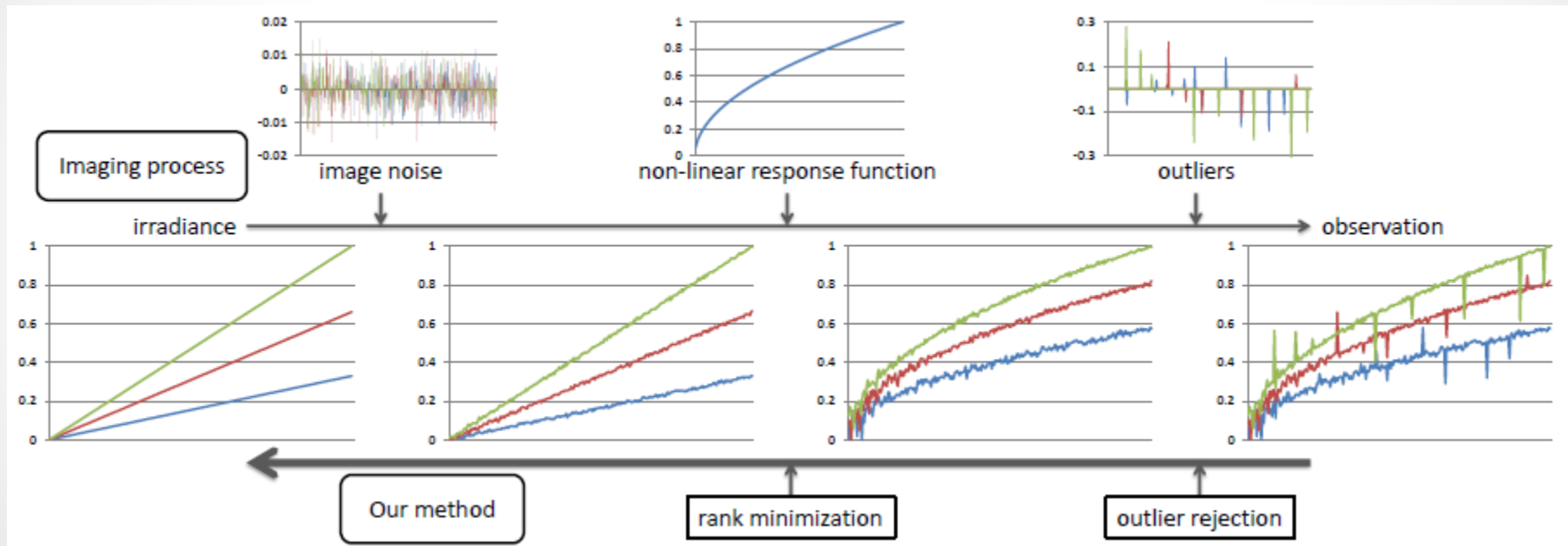


Varying illumination case



Rank of an irradiance matrix is one

Illustration of our approach

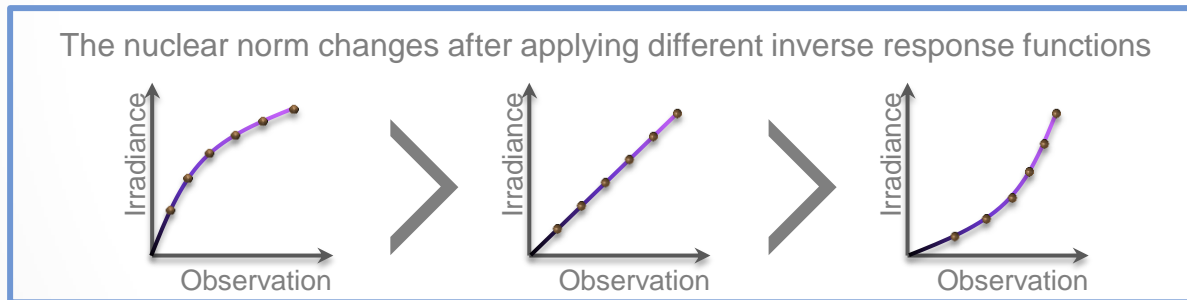


Benefits of rank minimization approach

- It can avoid the over-fitting problem
 - It does not rely on the ℓ^2 norm minimization
- It gives a unified framework for solving the radiometric calibration problem
 - Various radiometric calibration problems can be treated in the same manner
 - We explicitly use the linear dependency of the irradiance vectors
 - It gives a better understanding to the problem
- We can utilize an advanced rank minimization technique

Rank minimization

- Rank minimization
 - can be approximated as nuclear norm (sum of the singular values) minimization (J. Wright *et al.* NIPS'09)
- Response function changes not only the rank, but also the nuclear norm



- We minimize the condition numbers (a ratio of singular values)

$$\kappa_i \doteq \sigma_i / \sigma_1, \quad i = 2, 3, \dots, n$$

Rank variations

- Non-linearity of response function
 - monotonic and smooth curve
 - Only 2nd condition number has large value

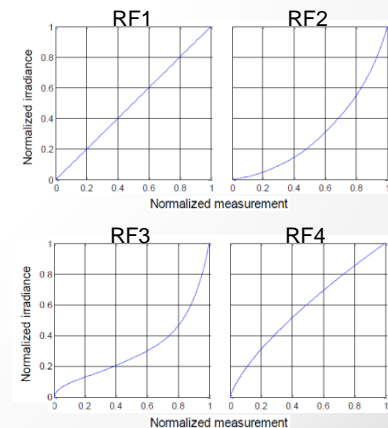
$$\kappa_2 \gg \kappa_3, \kappa_4, \kappa_5$$

- Image noisy
 - Signal-to-noise ratio: the higher condition numbers rapidly degrade
 - All the condition numbers are evenly affected

$$\kappa_2 \approx \kappa_3 \approx \kappa_4 \approx \kappa_5$$

→ $\min \kappa_{all}$ is susceptible to noise

condition number		κ_2	κ_3	κ_4	κ_5	κ_{all}
without noise	RF 1	0.0000	0.0000	0.0000	0.0000	0.0000
	RF 2	0.0284	0.0035	0.0009	0.0004	0.0332
	RF 3	0.1171	0.0186	0.0025	0.0000	0.1383
	RF 4	0.0028	0.0000	0.0000	0.0000	0.0028
with noise	RF 1	0.0178	0.0127	0.0097	0.0078	0.0480
	RF 2	0.0316	0.0157	0.0140	0.0123	0.0737
	RF 3	0.1181	0.0258	0.0150	0.0058	0.1646
	RF 4	0.0199	0.0107	0.0065	0.0044	0.0416



Calibration algorithm

- Minimize 2nd condition number to enforce rank-1 constraint
- Objective function

$$\hat{g} = \underset{g}{\operatorname{argmin}} \underbrace{\kappa_2(A)}_{\text{rank-1}} + \lambda \underbrace{\sum_t H\left(-\frac{\partial g(t)}{\partial D}\right)}_{\text{monotonicity}} \quad \text{s.t.} \quad A = g \circ D.$$

g : inverse response function

D : observation matrix

$$H(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Handling outliers

- Assumption
 - the Gaussian distribution of rank deviations from the rank-1 approximation
- Iteratively decompose input matrix into rank-1 and high-rank matrices
- Apply thresholding to the high-rank matrix according to the statistics of the high-rank matrix

Algorithm 1 Outlier Rejection Process

```
1: procedure OUTLIERREJECTION( $X, \rho$ )
2:    $Z_0 = X$ 
3:   while not converged do
4:      $(U, \Sigma, V) = \text{svd}(Z_k)$ 
5:      $R = U\Sigma_1V^T = \sigma_1u_1v_1^T$ 
6:      $N = Z_k - R$ 
7:      $dE = \Psi_\rho[N]$ 
8:      $Z_{k+1} = Z_k - dE$ 
9:   end while
10:  return  $Z^*$ 
11: end procedure
```

$$\Psi_\rho[h_i] = \begin{cases} h_i & \text{if } |h_i - \mu_H| > \epsilon + \rho s_H \\ 0 & \text{otherwise,} \end{cases}$$

Ambiguities

- Multiple-exposure case

- $\text{rank}(I) = 1 \rightarrow \text{rank}(I^\gamma) = 1$ for any γ
- *Exponential ambiguity*
- With at least one exposure ratio,

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}} \sum_{i,j} [\hat{g}^\gamma(M_i) - r_{i,j} \hat{g}^\gamma(M_j)]^2 \quad \text{where } r_{i,j} \text{ is the exposure ratio}$$

- Varying illumination case

- A certain class of response functions cannot be handled
 - $f(x)/f(ax) = \text{const.}$

- Color mixture case

- We cannot determine response functions when both
 - measured color distribution lies along the $R=G=B$ line
 - RGB channel responses are identical

Representation of response functions

- Empirical model of response function (EMoR)
 - Strong representation power with few coefficients
 - Difficult to compute derivatives due to non-smoothness
- Polynomial representation
 - Favorable to convex optimization due to smoothness
 - With explicit boundary conditions

$$g(t) = t + t(t-1) \sum_{i=1}^{n-1} c_i t^{n-i-1} \quad \text{※ Boundary conditions: } g(0) = 0 \text{ and } g(1) = 1$$

Prior model

- Insufficient information to estimate a unique solution
- Prior information
 - DoRF database
 - A multivariate Gaussian Mixture Model by EM
- Likelihood
 - Rank constraint
- MAP solution

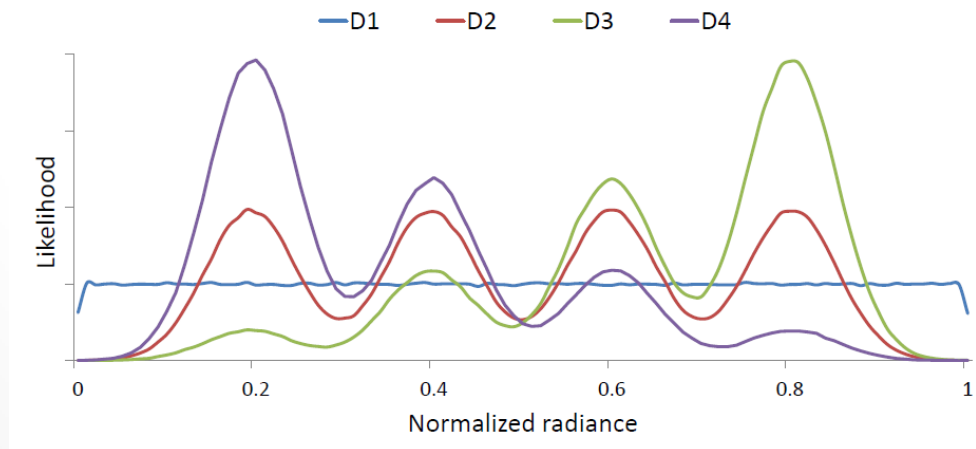
Experiments

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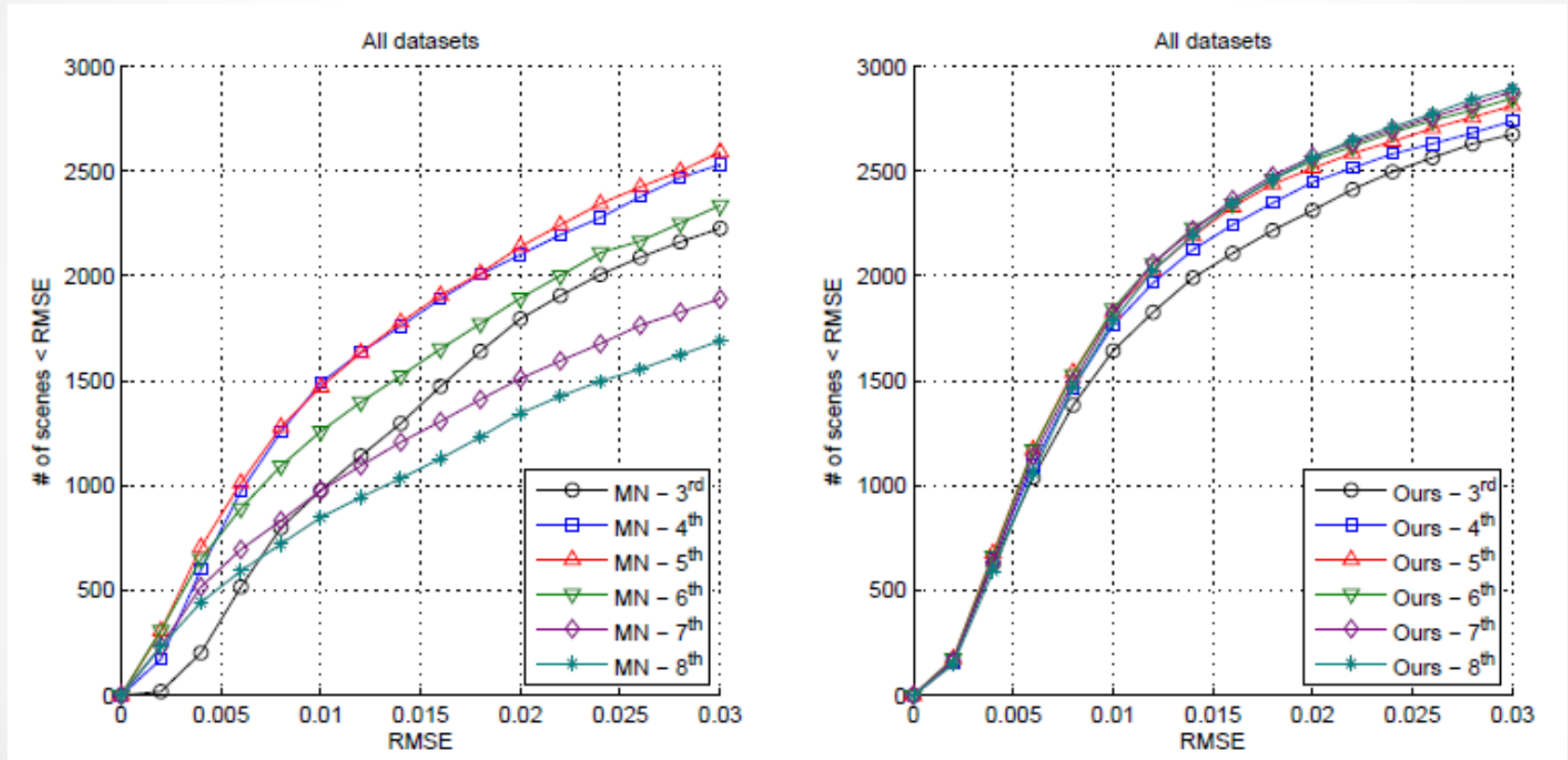
- Multiple-exposure case
 - ✓ Simulation
 - ✓ Real-world experiment
- Varying illumination case
- Color mixture case

Simulation

- Synthetic dataset
 - generated using a DoRF database (Grossberg and Nayar. *PAMI*'03)
 - 201 response functions
 - For each response function,
 - 1000 observations x 5 exposure times
 - 4 radiance distributions
 - 5 noise level: camera gains = $\{0, 1, 3, 6, 9\}$
 - 4020(= 201 x 4 x 5) synthetic data in total

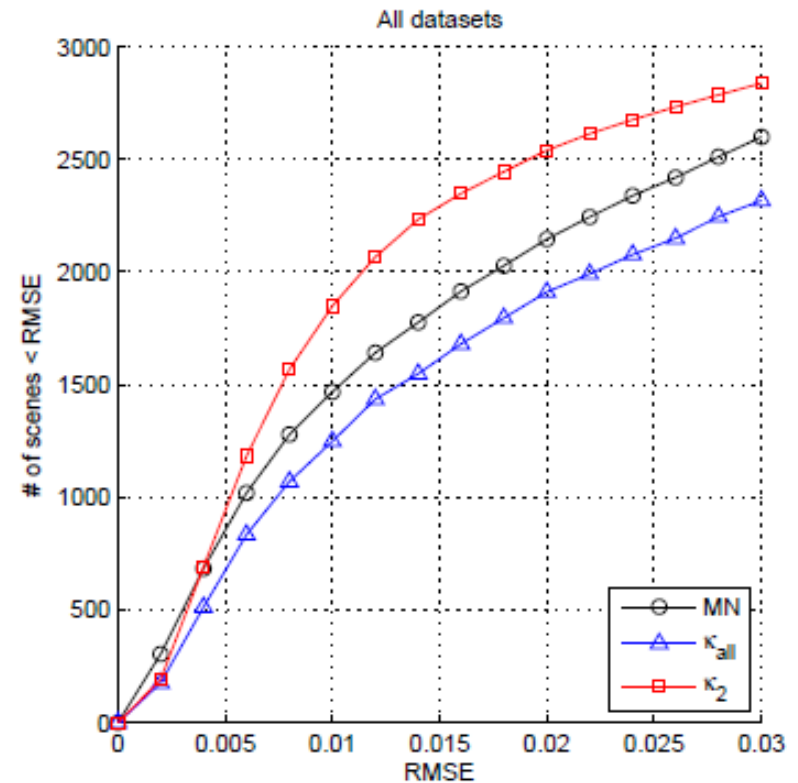
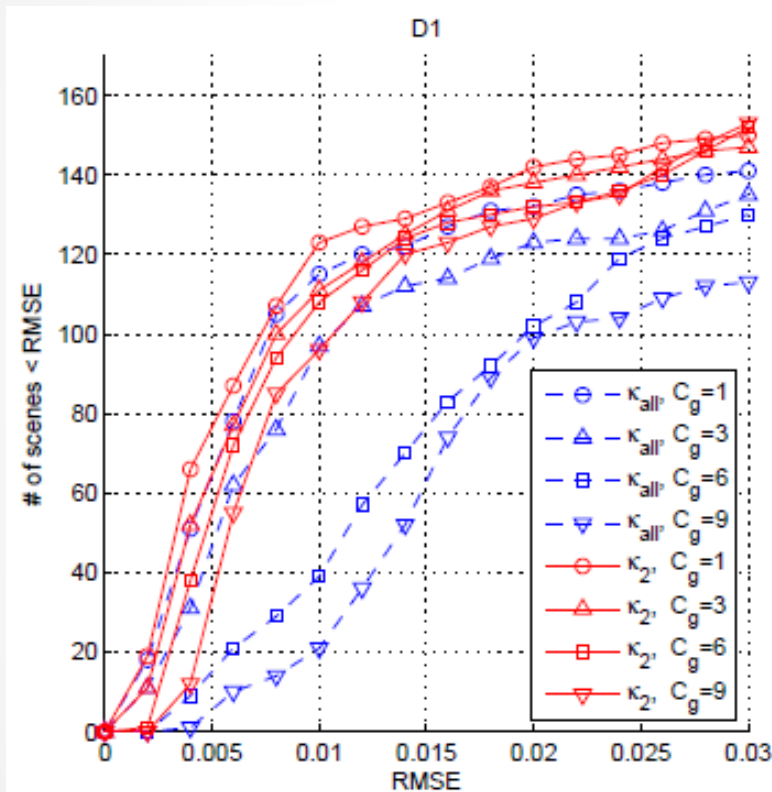


Number of coefficients



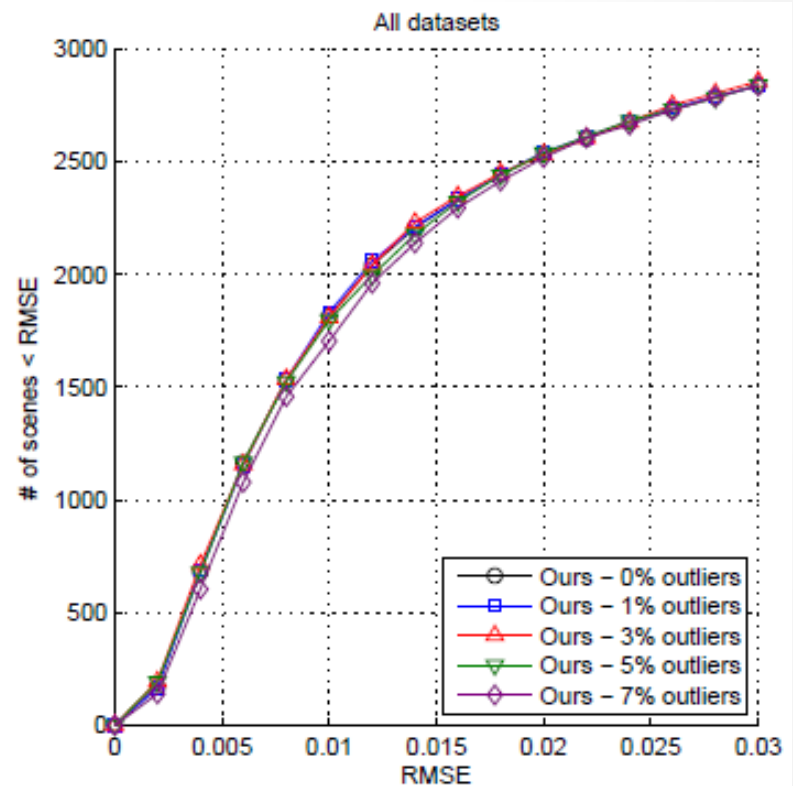
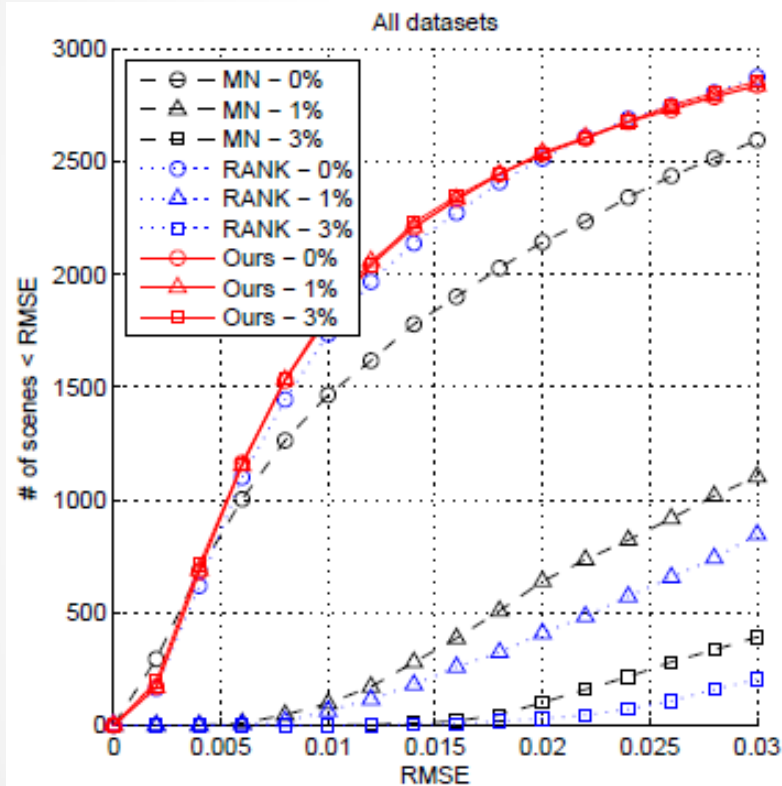
→ Use 5th order for MN, 6th order for Ours

Condition number and image noise



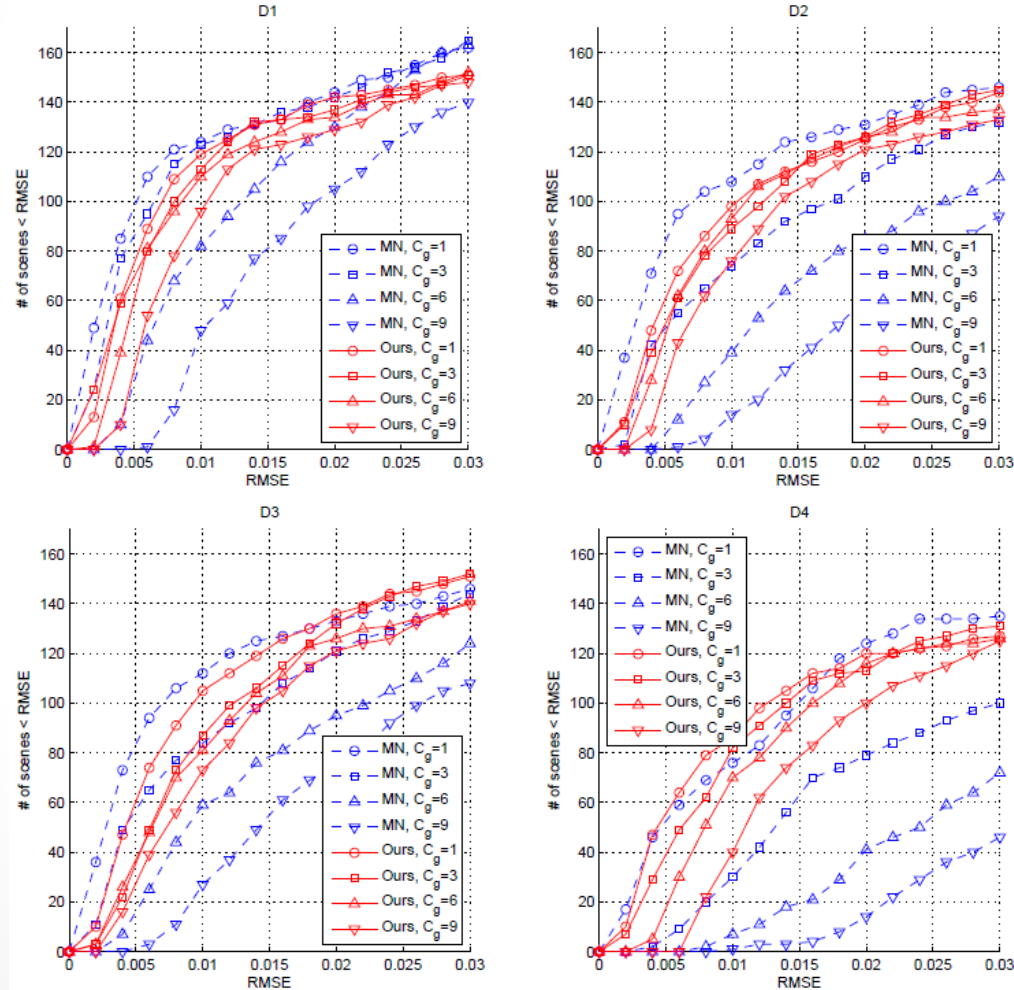
→ $\min \kappa_2$ is robust to noise, while $\min \kappa_{all}$ is susceptible

Outliers



→ With outlier rejection process, our method is robust to outliers

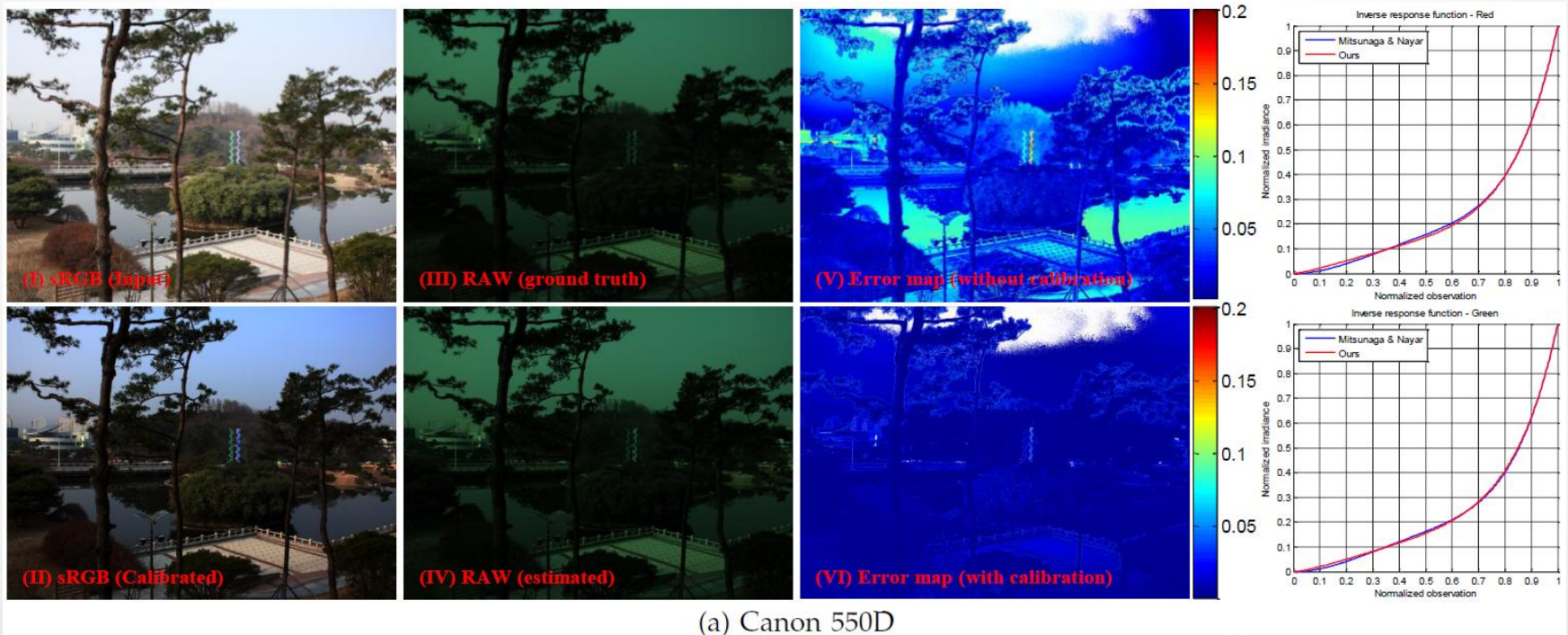
Comparison results (1)



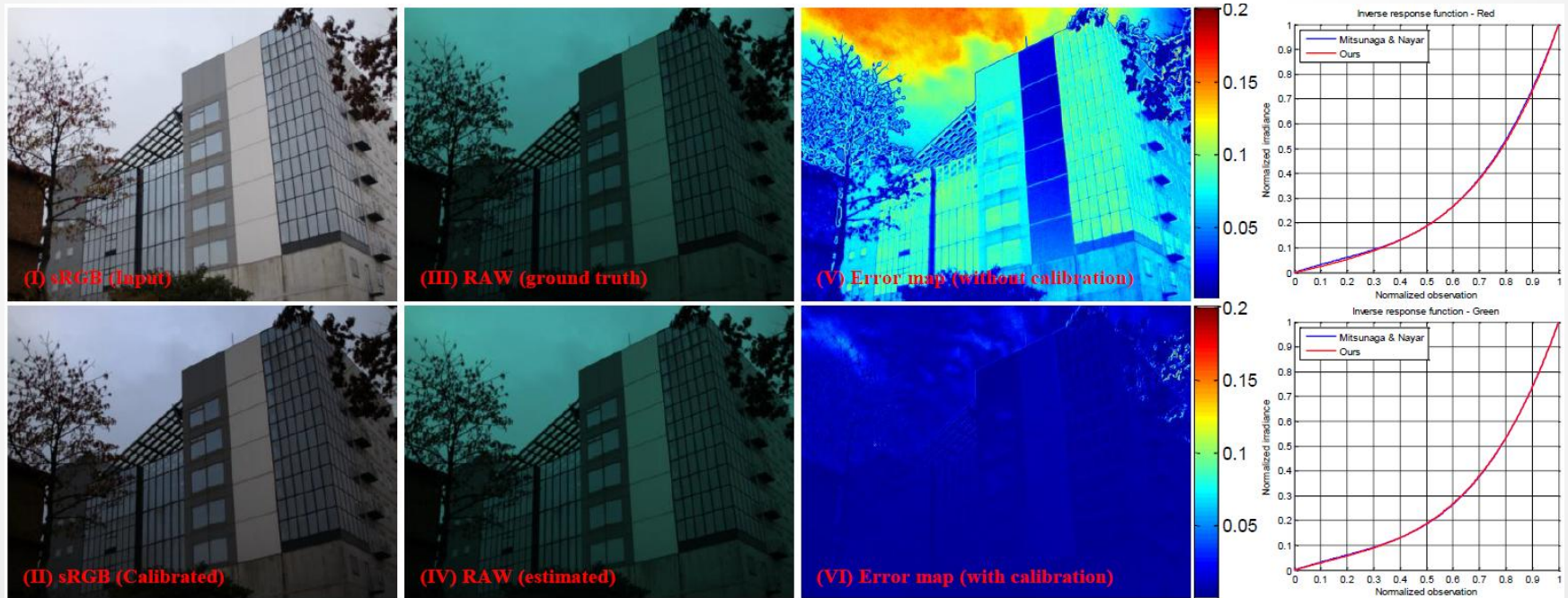
Comparison results (2)

Noise level (C_g)			Mean					Standard Deviation				
			0	1	3	6	9	0	1	3	6	9
D1	RMSE	MN	0.0058	0.0054	0.0062	0.0109	0.0160	0.0054	0.0057	0.0056	0.0063	0.0075
		Ours	0.0071	0.0070	0.0075	0.0084	0.0102	0.0054	0.0060	0.0067	0.0067	0.0070
	Disparity	MN	0.0142	0.0139	0.0152	0.0238	0.0354	0.0134	0.0140	0.0139	0.0147	0.0194
		Ours	0.0157	0.0164	0.0174	0.0194	0.0225	0.0124	0.0143	0.0153	0.0164	0.0179
D2	RMSE	MN	0.0079	0.0077	0.0134	0.0208	0.0287	0.0076	0.0081	0.0107	0.0133	0.0174
		Ours	0.0095	0.0100	0.0105	0.0111	0.0132	0.0082	0.0086	0.0083	0.0094	0.0098
	Disparity	MN	0.0180	0.0184	0.0299	0.0468	0.0634	0.0172	0.0190	0.0239	0.0304	0.0370
		Ours	0.0196	0.0214	0.0228	0.0240	0.0285	0.0163	0.0183	0.0186	0.0207	0.0227
D3	RMSE	MN	0.0076	0.0074	0.0111	0.0174	0.0234	0.0072	0.0080	0.0092	0.0117	0.0141
		Ours	0.0080	0.0086	0.0105	0.0116	0.0128	0.0066	0.0069	0.0068	0.0086	0.0085
	Disparity	MN	0.0170	0.0176	0.0250	0.0398	0.0521	0.0164	0.0180	0.0207	0.0282	0.0309
		Ours	0.0173	0.0184	0.0218	0.0245	0.0272	0.0142	0.0139	0.0137	0.0182	0.0193
D4	RMSE	MN	0.0086	0.0118	0.0233	0.0393	0.0565	0.0079	0.0097	0.0152	0.0252	0.0344
		Ours	0.0144	0.0131	0.0138	0.0154	0.0189	0.0138	0.0134	0.0124	0.0118	0.0126
	Disparity	MN	0.0195	0.0262	0.0507	0.0822	0.1155	0.0184	0.0221	0.0331	0.0486	0.0635
		Ours	0.0285	0.0275	0.0293	0.0327	0.0393	0.0270	0.0276	0.0273	0.0275	0.0308

Real-world experiment (1)

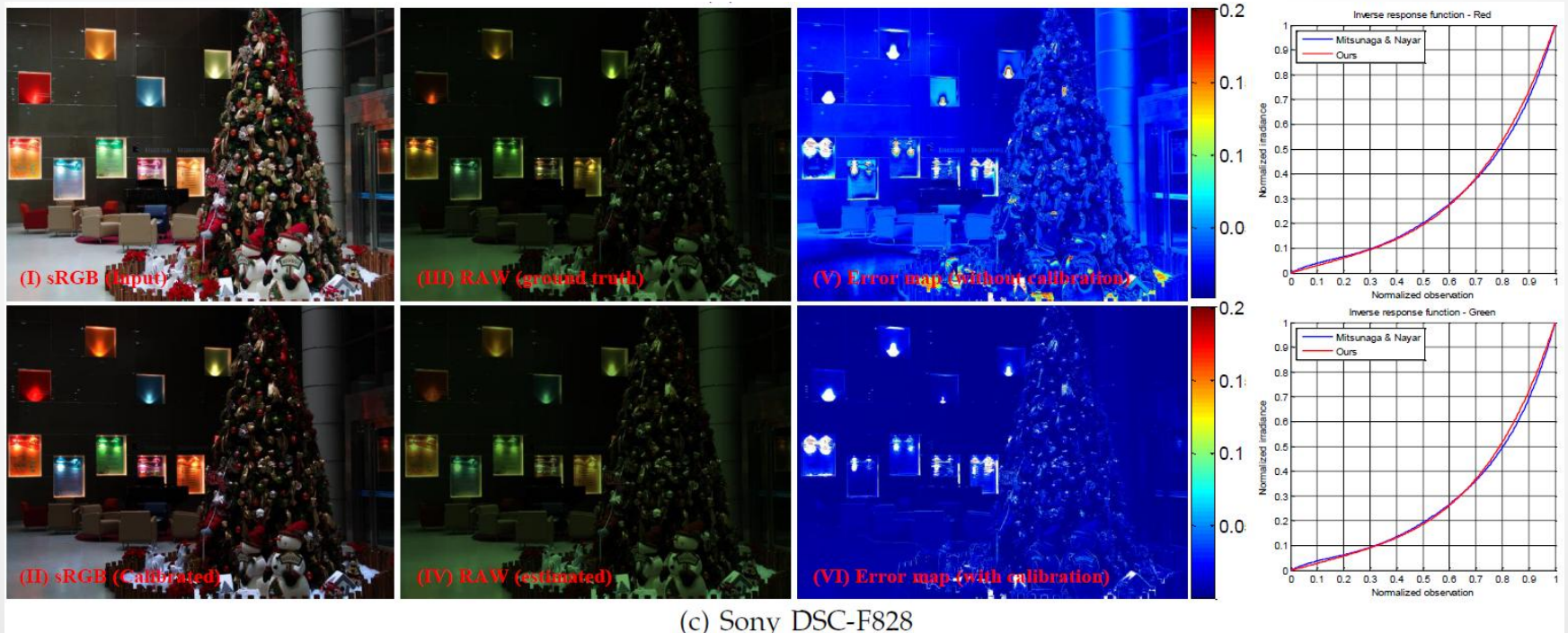


Real-world experiment (2)



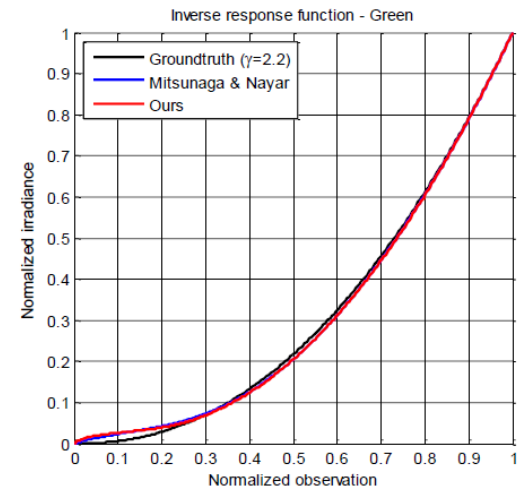
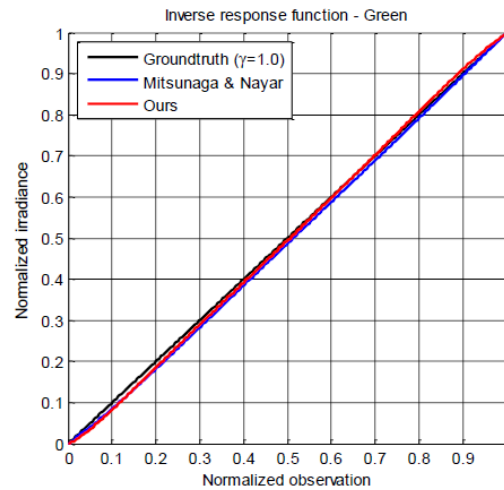
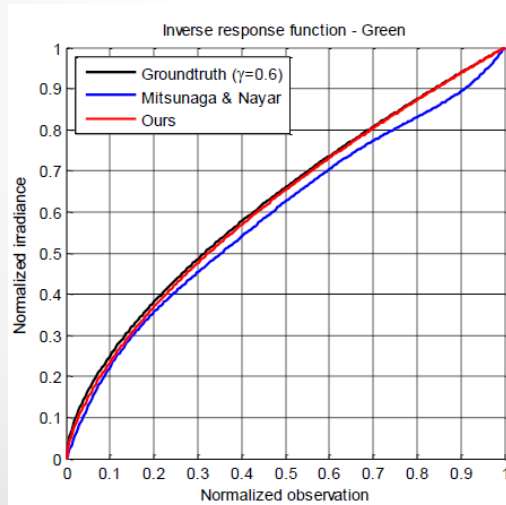
(b) Nikon D1X

Real-world experiment (3)



Real-world experiment (4)

- Point Grey Flea3
 - Three different gamma response functions

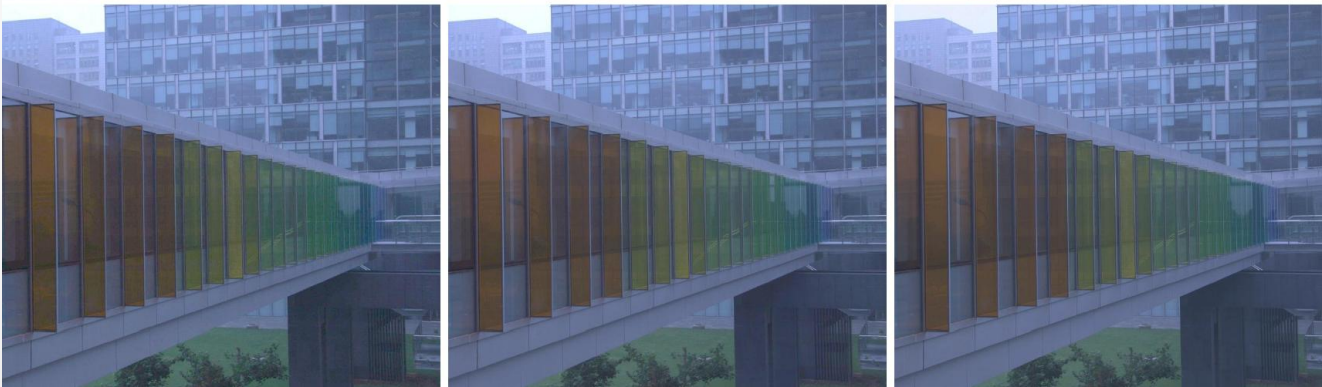


Radiometric Alignment

- No exposure information is used

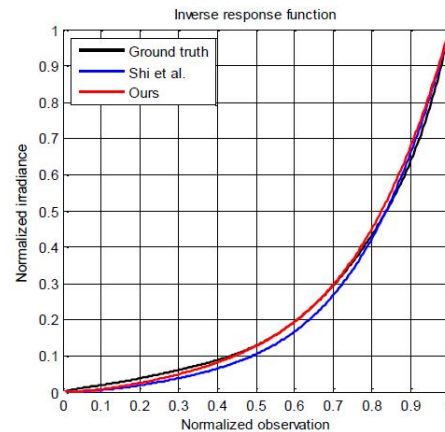


Input images

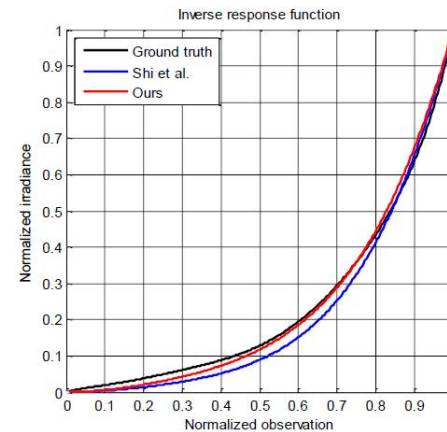


Aligned images

Varying illumination case



SHEEP (12)



FROG (20)

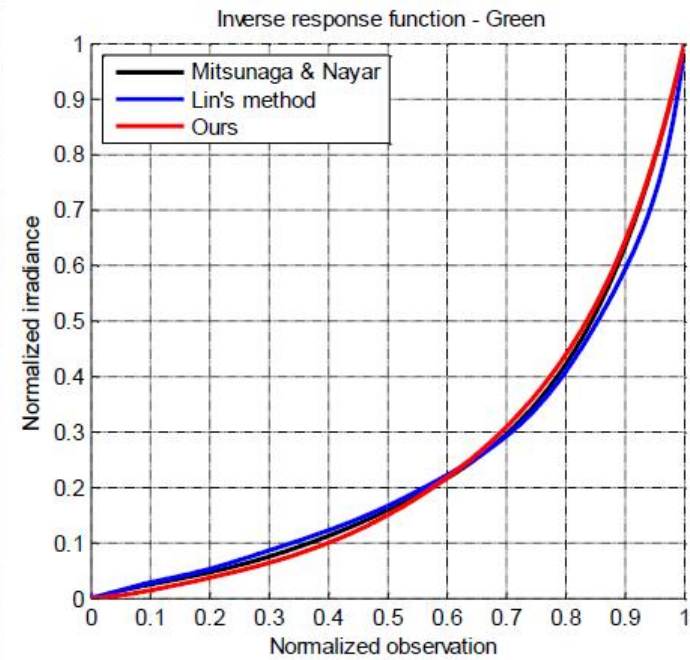
Dataset		SHEEP (Canon 20D)			FROG (Nikon D70)		
samples	method	RMSE (std.)	Disparity (std.)	Time(s)	RMSE (std.)	Disparity (std.)	Time(s)
50	Shi <i>et al.</i> [4]	0.0488 (0.0227)	0.0846 (0.0429)	433.66	0.0279 (0.0050)	0.0456 (0.0064)	697.05
	Ours	0.0226 (0.0006)	0.0447 (0.0061)	0.84	0.0191 (0.0010)	0.0419 (0.0051)	0.80
100	Shi <i>et al.</i> [4]	0.0418 (0.0172)	0.0729 (0.0345)	914.64	0.0293 (0.0038)	0.0441 (0.0056)	1316.88
	Ours	0.0218 (0.0003)	0.0430 (0.0021)	1.11	0.0176 (0.0005)	0.0396 (0.0032)	0.86

Color mixture case

Rank error function

$$E(g; D) = \sum_{i=1}^m w_i \kappa_2(A_i) \quad \text{s.t.} \quad A_i = g \circ D_i$$

ω_i : the distance between the two irradiances in the RGB space



Summary

- We introduce radiometric calibration framework that use the low-rank structure of irradiance matrix
- Radiometric calibration is formulated as rank minimization and solved by the condition number minimization
- We developed an algorithm for outlier rejection
- Our method can avoid over-fitting
- Our method can be applied to various kind of radiometric calibration problems

Q & A

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Thank You for attention!