Color Constancy: How to Deal with Camera Bias?

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Background

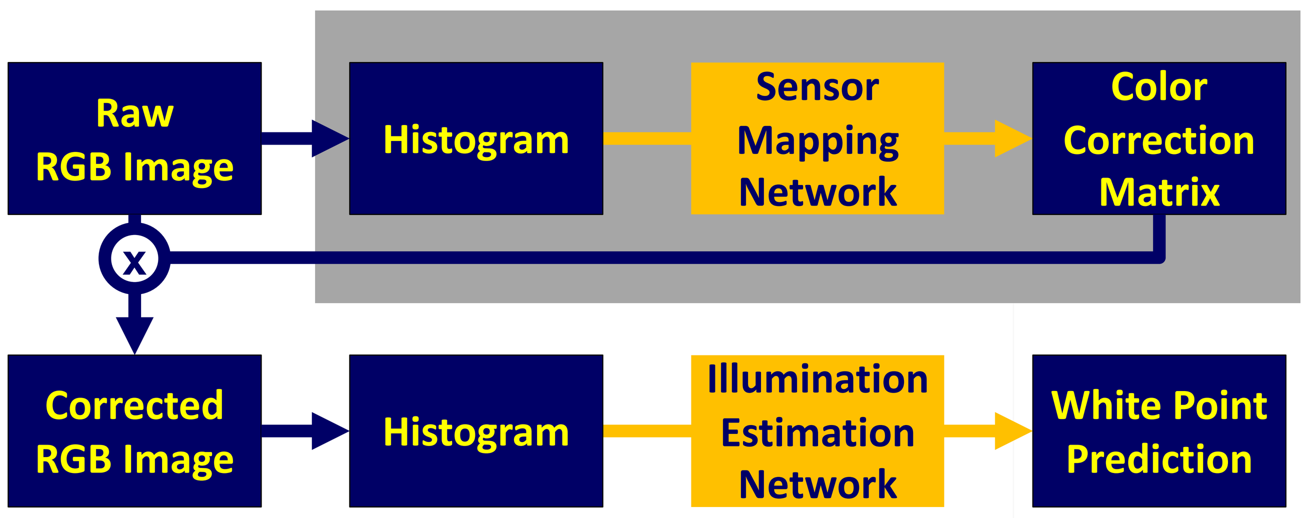
- Color constancy: **estimate the light source color from each raw RGB image**.
- Machine learning performs better than image-statistics-based methods.
- Camera bias: learning methods might fail when **used on a different camera**.

Current Solutions: 2x - 3x Larger Networks

- SIIE [1]

With gray part FLOPS = **310 M**

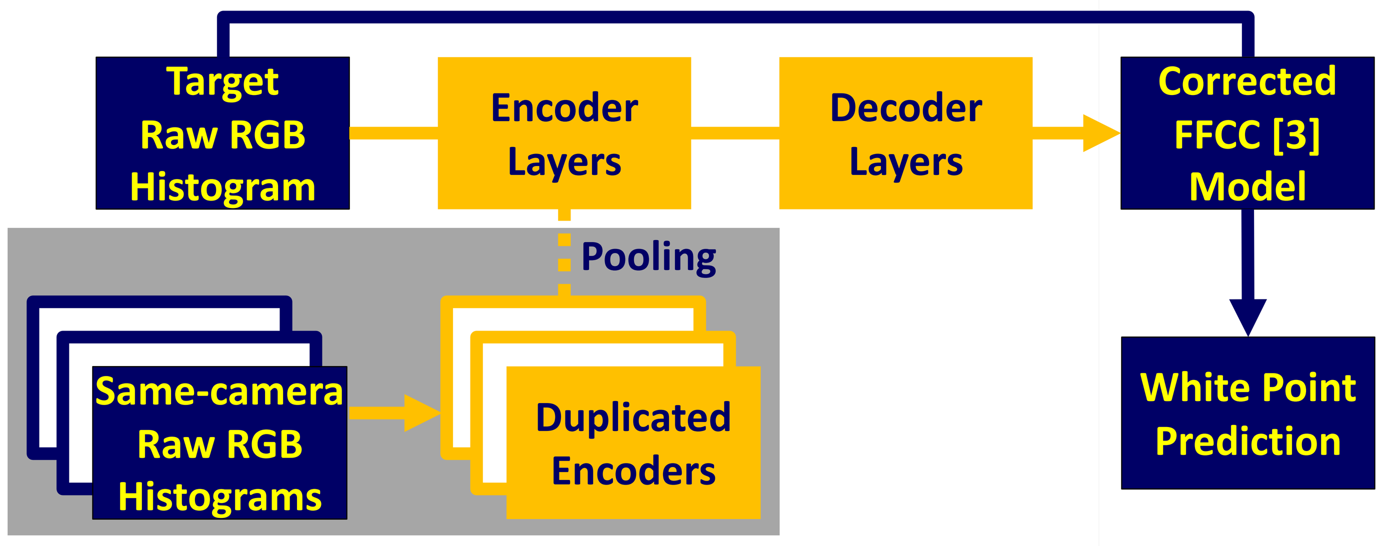
Without gray FLOPS = **155 M**



- C5 [2]

With gray part FLOPS = **145 M**

Without gray FLOPS = **51 M**



Problem Definitions

- **SIIE & C5 use most of the FLOPS to solve camera bias**, not color constancy.
- Is there a simpler solution if some camera characterization data is available?
  - ➢ Something like the CCM: obtained in the camera manufacturing process, light weighted, and fast processing.
- Can SIIE and C5 be further improved and/or simplified?

Proposed Solution: "Color Homography" [4]

$$\frac{1}{\alpha}\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}\begin{bmatrix} R_1/G_1 \\ B_1/G_1 \\ 1 \end{bmatrix} \approx \begin{bmatrix} R_2/G_2 \\ B_2/G_2 \\ 1 \end{bmatrix}$$

Compensating scalar (keep the 3rd component of $\mathbf{H}\underline{\mathbf{c}}_1 = 1$)

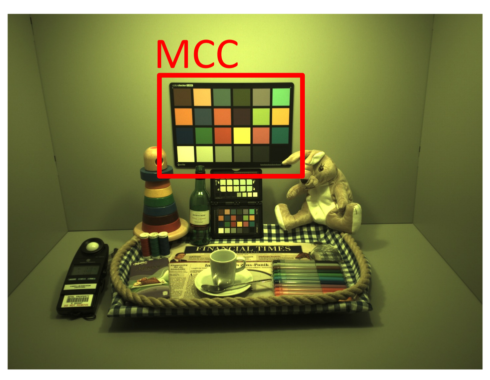
Fixed matrix for this camera pair $\mathbf{H}$

Camera 1 color at a pixel $\underline{\mathbf{c}}_1$

Camera 2 color at the same pixel $\underline{\mathbf{c}}_2$

- Optimizing $\mathbf{H}$
  - ➢ **Macbeth ColorChecker** captured by Camera 1&2 under the same light(s)
  - ➢ Example: INTEL-TAU database [5]

Camera 1 = Canon 5DSR SpectraLight Illuminant A



Camera 2 = Sony IMX135 SpectraLight Illuminant A

MCC patch ID i

$$\min_{\mathbf{H}} \sum_{\ell=1}^{L}\sum_{i=1}^{24} \left|\left| \frac{1}{\alpha^{(i,\ell)}}\mathbf{H}\underline{\mathbf{c}}_1^{(i,\ell)} - \underline{\mathbf{c}}_2^{(i,\ell)} \right|\right|_2^2$$

when using more than 1 lights ℓ

- Using $\mathbf{H}$ on real scenes

Scene captured by Canon 5DSR

$\xrightarrow{\mathbf{H}}$

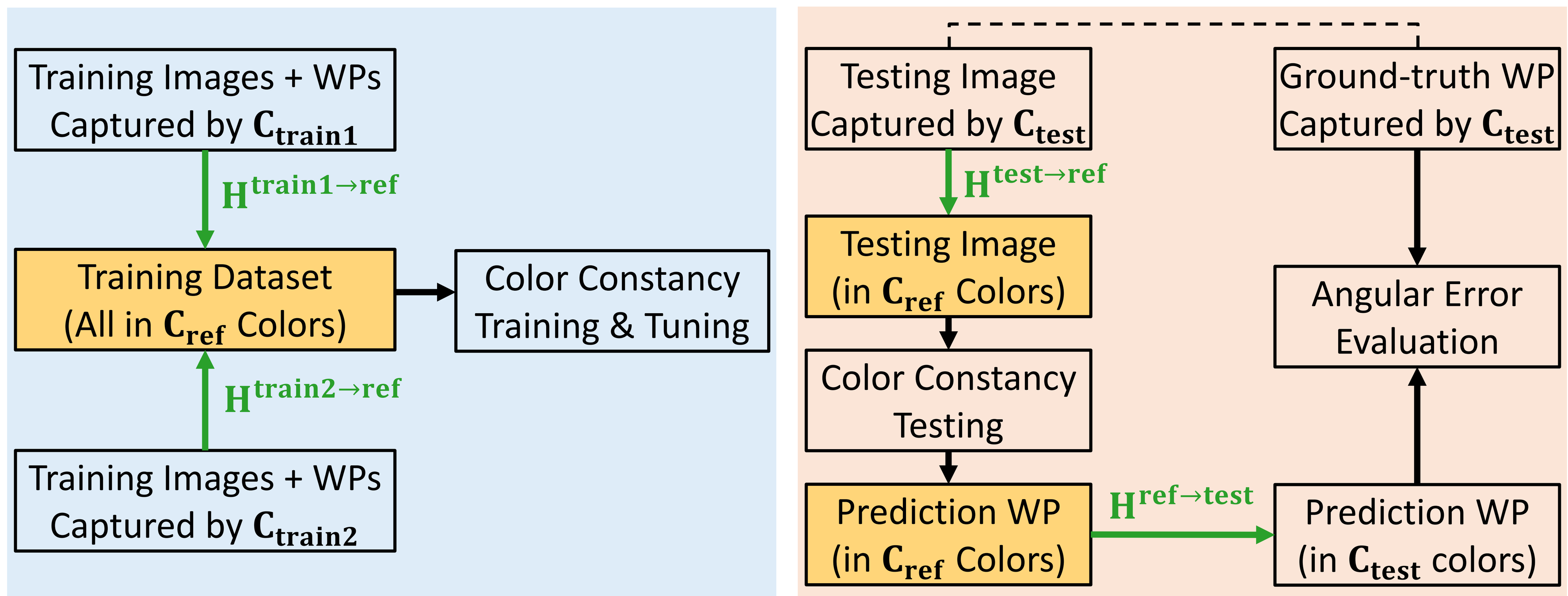
Canon scene mapped to Sony IMX135 colors

Scene actually captured by Sony IMX135

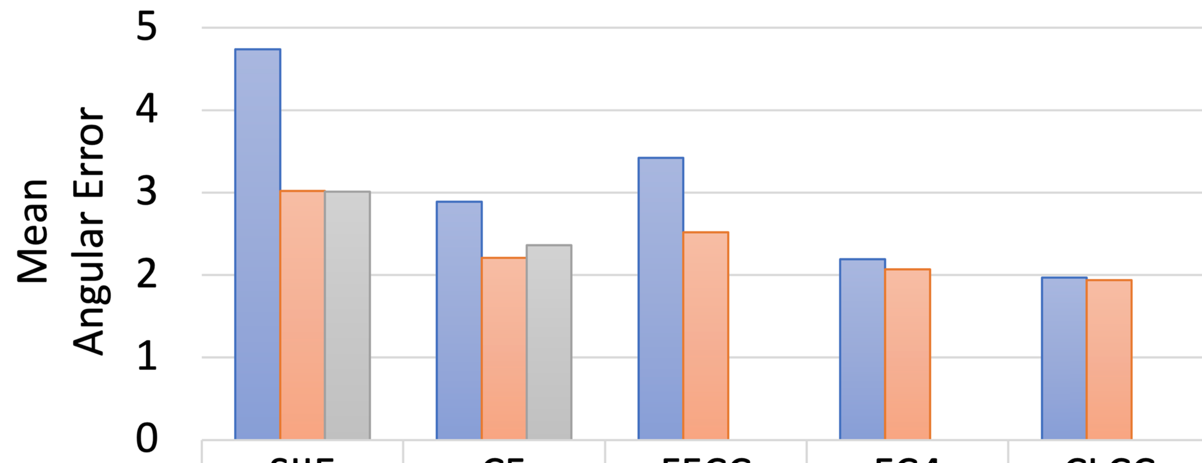
*The work was performed when Jun Hu worked at Meta and during Yi-Tun's internship with Meta.

Experiment

- INTEL-TAU database
  - ➢ **3 camera models**, ~1600 – 2300 different scenes each for training
  - ➢ 2 cameras for training, 1 for testing (same-scene images incl. in testing)
  - ➢ MCC images in 10 different lights for obtaining $\mathbf{H}$ for all camera pairs
- Homographic-corrected color constancy
  - ➢ $\mathbf{C}_{\mathbf{ref}}$ is a chosen reference camera



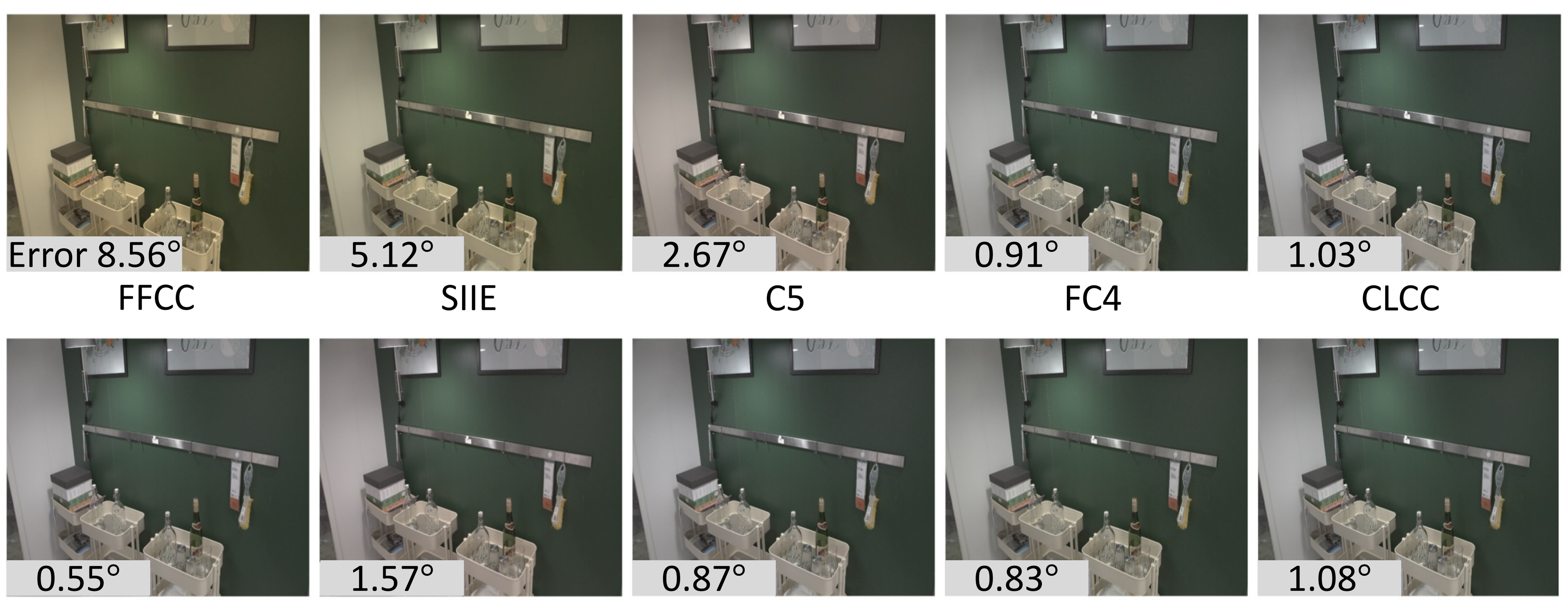
Results



	SIIE	C5	FFCC	FC4	CLCC
Original	4.74	2.89	3.42	2.19	1.97
Homography	3.02	2.21	2.52	2.07	1.94
Homography + Simplified	3.01	2.36			

Cross-camera methods (SIIE, C5) — Single-camera methods (FFCC, FC4, CLCC)

- SIIE and C5 are improved significantly by homography.
  - ➢ They only learned to **partially** solve the camera bias issue.
- Not only improve, homography can **replace** a large part of SIIE and C5.
- Homography also improves other single-camera algorithms.
  - ➢ FC4 [6] and CLCC [7] are huge networks (6.5G – 7.3G FLOPS).
  - ➢ Strong data augmentation might already help solving camera bias.



FFCC | SIIE | C5 | FC4 | CLCC

FFCC (homog) | SIIE (homog) | C5 (homog) | FC4 (homog) | CLCC (homog)

Conclusion & Key Messages

- Algorithms claimed to be "cross-camera" only solve the issue partially.
- Color homography is a simpler and better way to solve camera bias.
- Aggressive data augmentation used in large networks might also help, but there is risk of not covering all camera models (TBC in future work).

References

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[7] Lo *et al.* CLCC: contrastive learning for color constancy. In CVPR, 2021.