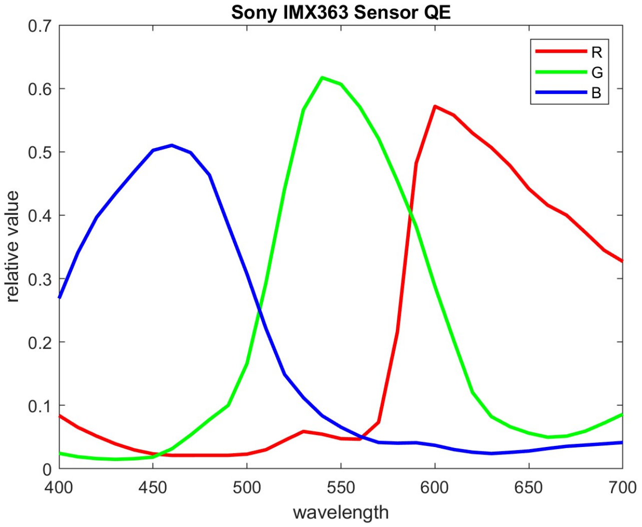
Sensor QE Estimation Methodologies - Nikhil Parab

Introduction

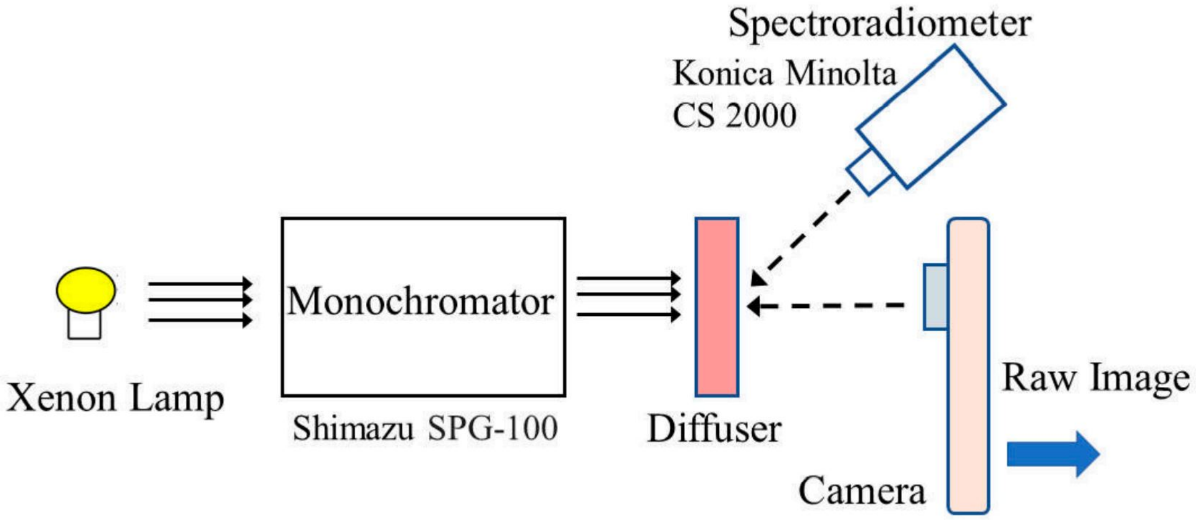
Camera sensors convert the incident photons into electrons. However, not all incident photons are converted into electrons. The percentage of incident photons converted to electrons is defined as the image sensor's spectral quantum efficiency (QE). Image Sensor QE depends on the structure and material of the sensor and represents the image sensor output per unit incident light energy wavelength within the spectral operational range of the sensor. The figure below shows an example sensor QE for the Sony IMX363 camera sensor.



Knowledge of sensor spectral efficiency is vital for many imaging applications and several methods for measuring and estimating spectral sensitivity have been developed. For our project, we plan to study, validate and compare the results from two recently published papers that propose novel methodologies for estimating QE. Our project goal is to find which methodology gives the most stable and accurate QE estimation results without the need for an expensive, time-consuming process.

Background

Knowledge of camera spectral efficiency is critical to many fields that deal with images, such as imaging science, computer vision, medical imaging, robotics, and autonomous driving. A standard direct approach for computing sensor QE for a given camera sensor involves measurement of the spectral sensitivity at each wavelength using a monochromatic light source. The figure below shows an example laboratory setup for directly measuring the camera sensor QE.



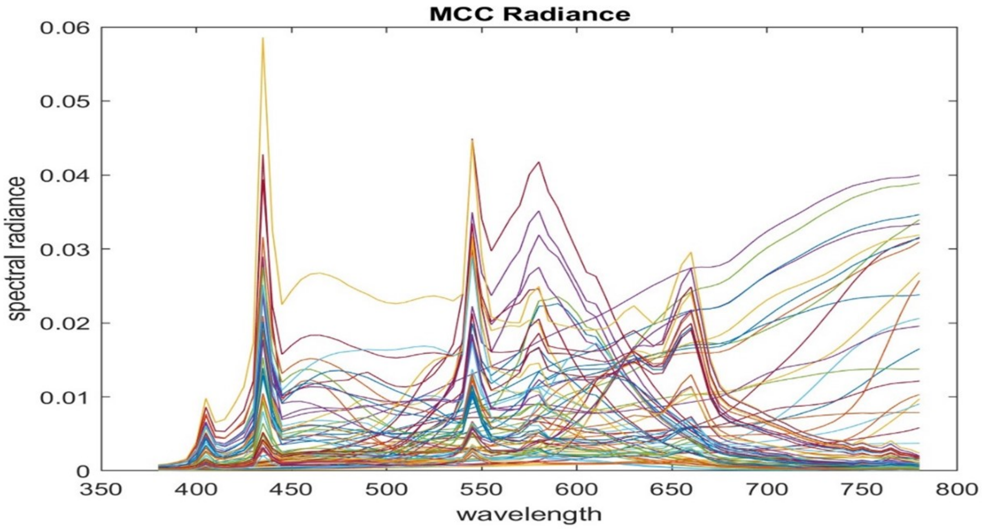
This method is accurate but expensive, time-consuming, and requires a laboratory setting. As a result, another less accurate but simpler sensor QE estimation method has been developed using color samples (e.g. Macbeth Color Checker). This method is based on a pair comprising the surface spectral reflectance of standard color samples under different illuminants and corresponding output captured data of sensor RGB values. This method involves solving a system of linear equations. It depends on the measurements to be linearly independent and of the order of the dimensionality of the spectral sensitivity function for accurately estimating the results. As the surface spectral reflectance of natural or human-made objects is described using six to eight basis functions, the dimensionality of reflectance is much lower than the dimensionality of the spectral sensitivity function resulting in inconsistent and inaccurate results. Two recently published papers attempt to address these limitations by proposing novel methodologies which work well with a limited dataset, provide stable, accurate results and do not require expensive, time-consuming setups. In the following sections, we plan to review these two methodologies in detail and reproduce the published experiment results with our dataset.

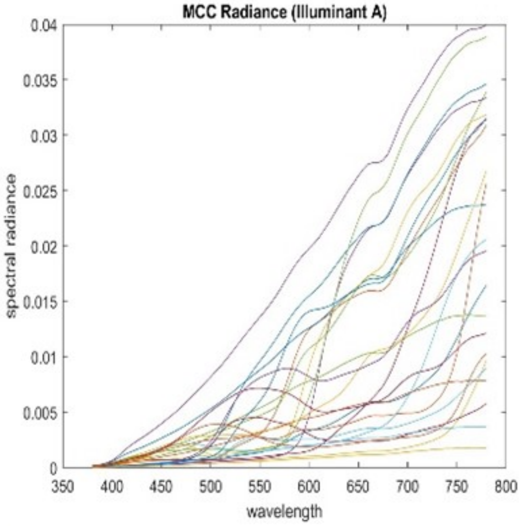
DATASET

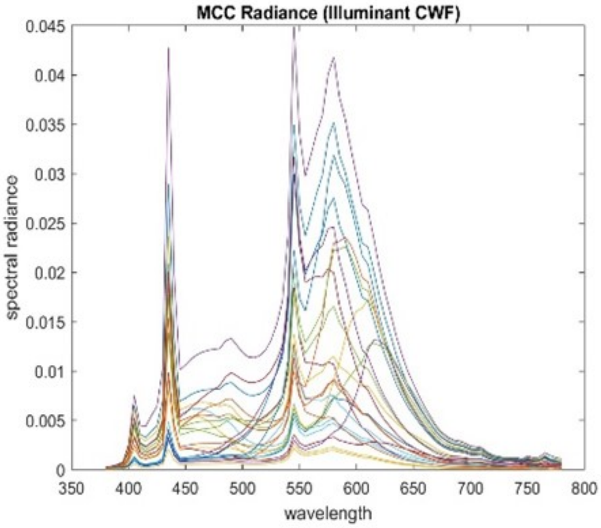
For reproducing and evaluating the results from the papers, we plan to use the spectral radiance measurements of Macbeth Color Checker (MCC) and the corresponding simulated sensor RGB response under the following three illuminants.

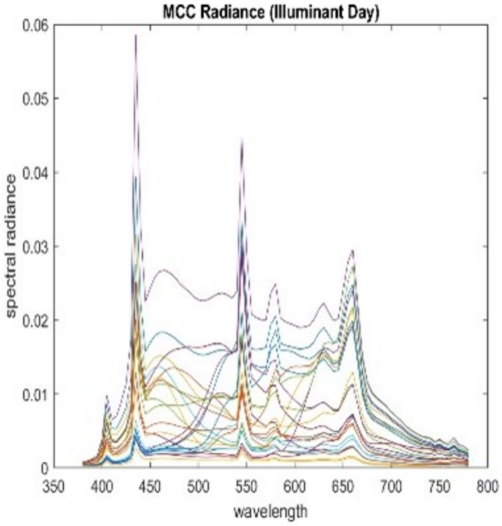
- Tungsten light (A)
- Cool White Fluorescent (CWF)
- Daylight (Day)

MCC Spectral Radiance under three illuminants

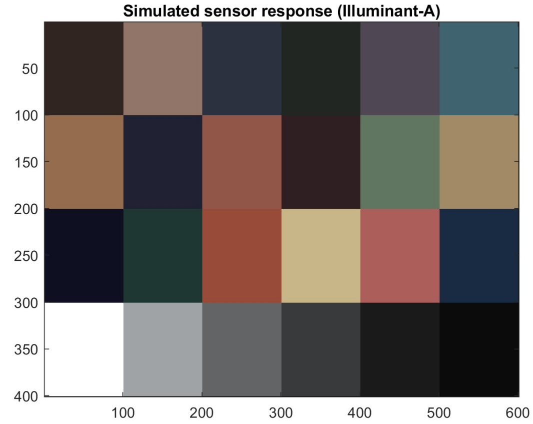


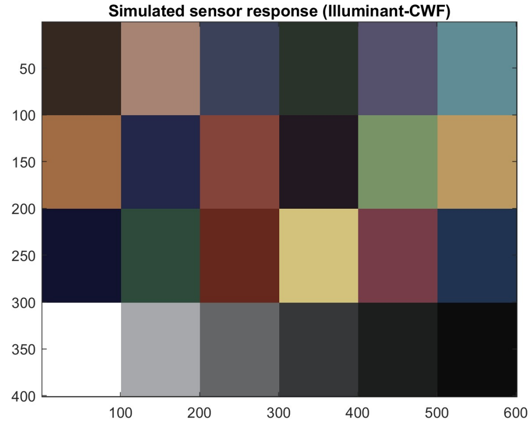


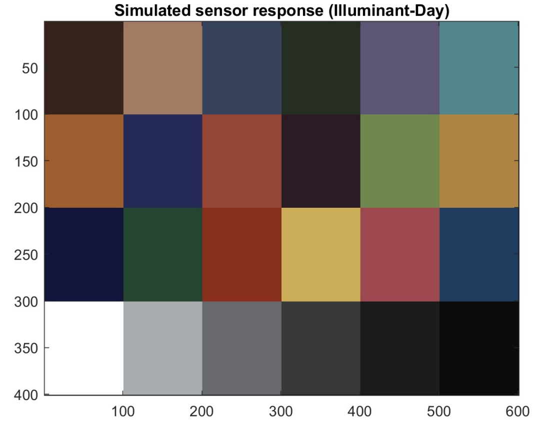




Simulated Camera Sensor Response under three illuminants



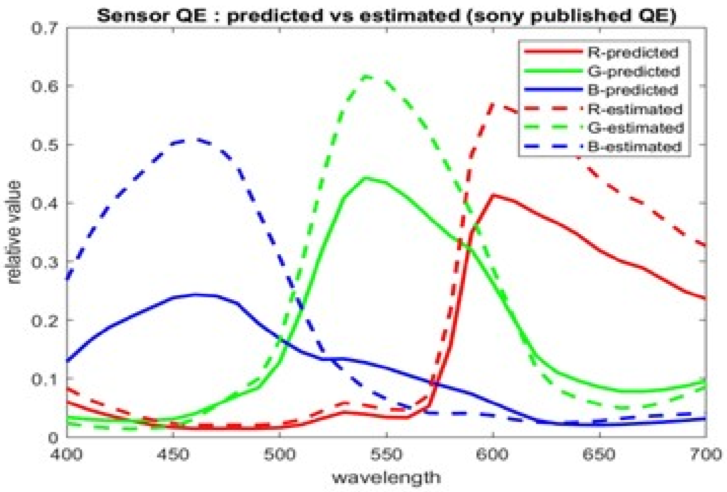


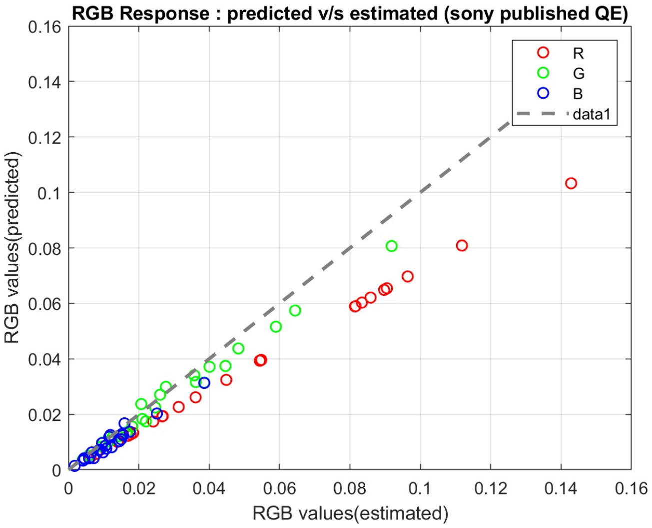


METHOD

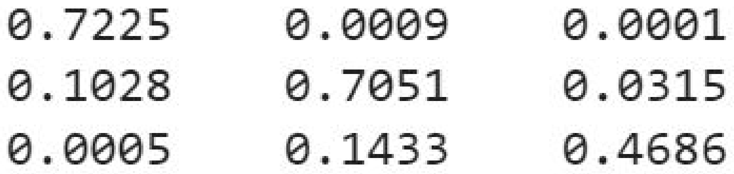
QE Estimation Method-1 [published QE as basis vectors]

A recently published paper from Stanford [1] proposes a novel methodology for solving the QE estimation problem when we have some additional information about the sensor provided by the manufacturer. This methodology is based on directly using the published sensor QE as the basis for estimating sensor response. Using Macbeth Color Chart (MCC) radiance data under single illuminant-A and corresponding simulated sensor RGB response values, we were able to successfully reproduce the results from the paper and confirm that the published sensor QE response differs from the predicted QE response as shown in the below.



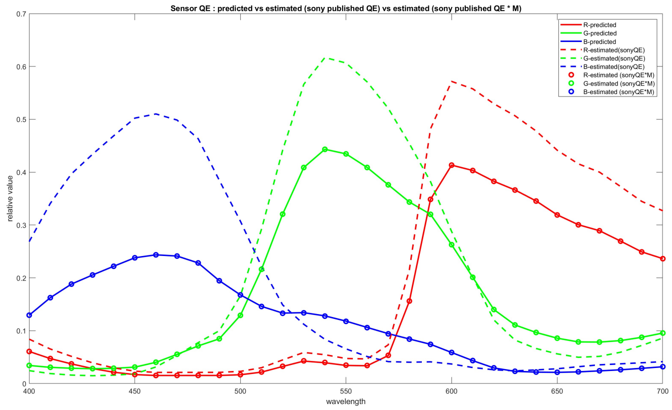


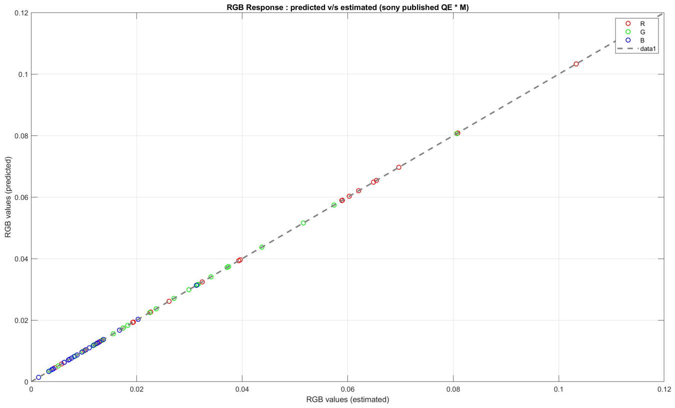
This substantial difference in the estimation results is due to the sensor optical crosstalk and channel gains which the published sensor QE does not consider. To account for these factors, we found a positive 3x3 matrix, M, to transform the published sensor QE. This matrix was estimated by minimizing the least square error between the published RGB response and the estimated RGB response samples subject to a non-negativity constraint under illuminant-A. The fit matrix is given by



$$\begin{matrix} 0.7225 & 0.0009 & 0.0001 \\ 0.1028 & 0.7051 & 0.0315 \\ 0.0005 & 0.1433 & 0.4686 \end{matrix}$$

The diagonal entries of this matrix represent the channel gains, and the off-diagonal elements represent the sensor channel crosstalk. For example, one significant non-diagonal value of 0.1 in this matrix represents red and green channel crosstalk in the output G estimate. After accounting for these optical crosstalk and color channel gain corrections in the published sensor QE, we can accurately estimate the QE response as shown in the results below. The results below show the estimated QE fits well with the predicted one and, the estimated response falls along the identity line with the predicted response.



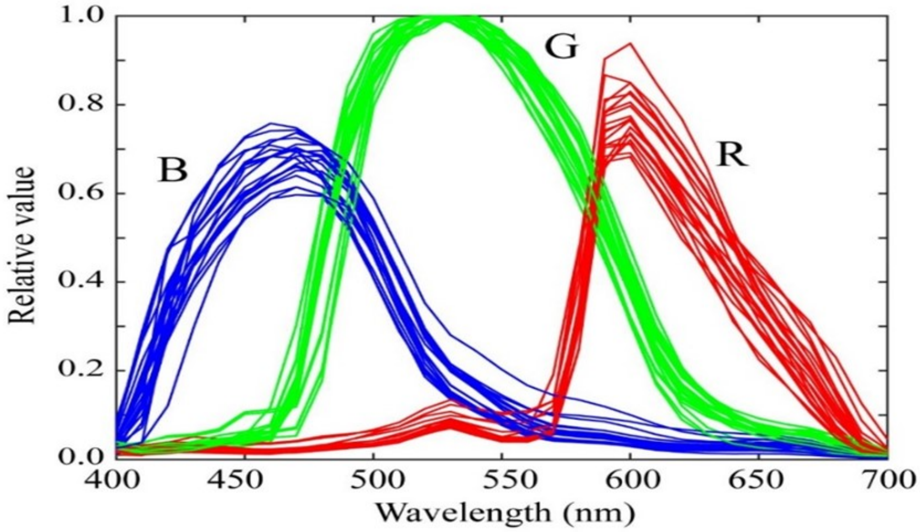


QE Estimation Method-2 [Principal Component Analysis (PCA) algorithm]

Another recently published paper [2] by Tominaga proposes a simple and novel methodology for solving sensor QE estimation problem using the spectral statistical features extracted from a database of sensitivity functions.

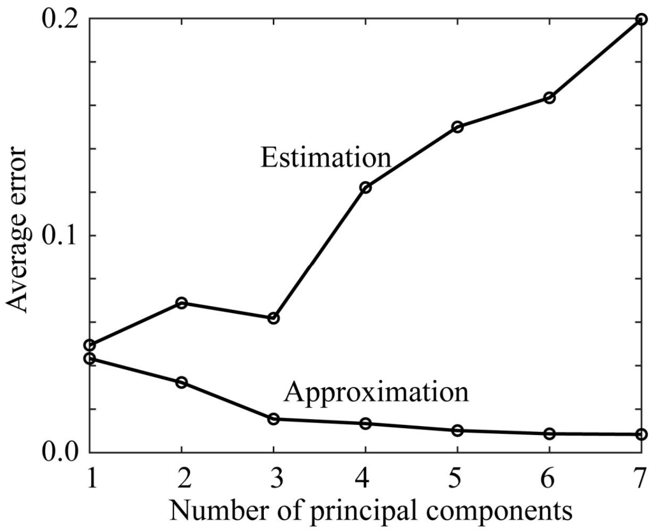
The PCA based Camera Sensitivity Estimation Algorithm flow is described as follows.

1. A database of the measured spectral sensitivity functions of several mobile phone camera sensors is constructed. Plotting these curves, we can observe that there is no significant variance in these QE curves. The sharp drop in the red channel QE response is due to the Infrared cut-off filter present in the mobile cameras to reflect or block near-infrared wavelengths and produce realistic colors as perceived by the human visual system.

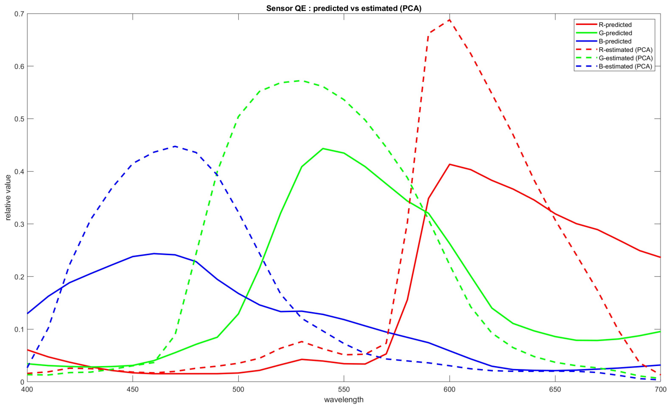


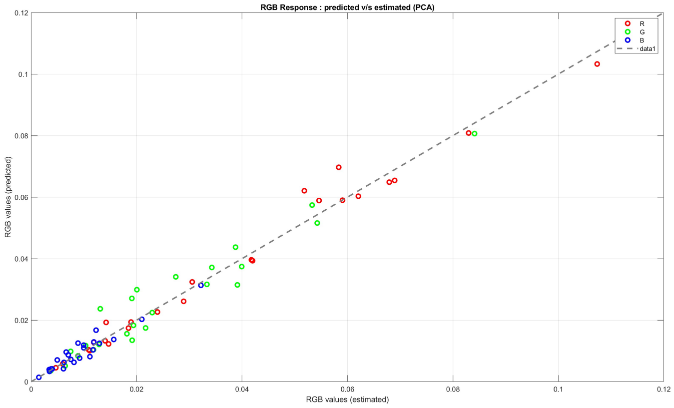
2. Principal Component Analysis (PCA) is applied to this database of sensitivity functions to statistically determine the dimensionality of the spectral data and extract the key features representing the spectral shape of the data.
3. Singular Value Decomposition (SVD) is used for PCA as it provides an orthogonal decomposition of the spectral database. Thus, each measured spectral sensitivity function is uniquely expressed as a linear combination of these orthogonal vectors i.e. the principal components.
4. On further analysis, it can be found that the spectral sensitivity functions can be approximated using the first three principal components with sufficient accuracy (99.9%).
5. These principal components are used as basis vectors (constraints) in the estimation method using the standard least square approximation method with a non-negative constraint performed on a single illuminant pair of (surface reflectance, RGB response) dataset.

6. The selection of the number of principal components directly impacts the accuracy of the QE estimation results.
7. Another interesting finding from the analysis and experiment results is that the measured spectral sensitivity functions can be most accurately estimated solely based on the first principal component of this database. The reasoning for this is that the values of second or higher (> 2) principal components are very small indicating that it has a very small contribution which can be considered as noise.



Thus, it was concluded that the spectral sensitivity of any mobile camera can be accurately estimated solely based on the first principal component of the database with a small dataset of color samples. Following are the sensor QE estimation results using the above algorithm based on PCA.

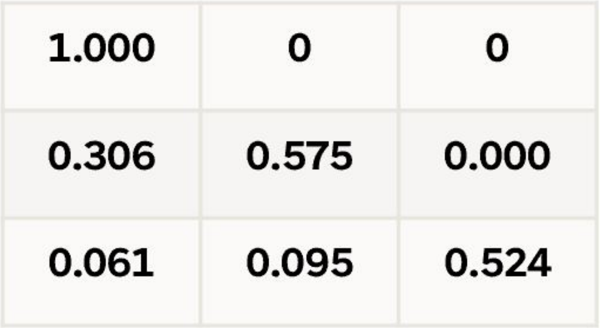




Experiment results above show that the PCA algorithm gives more accurate QE response compared to method-1 without 3x3 correction.

QE Estimation Method-2 improvement [3x3 correction]

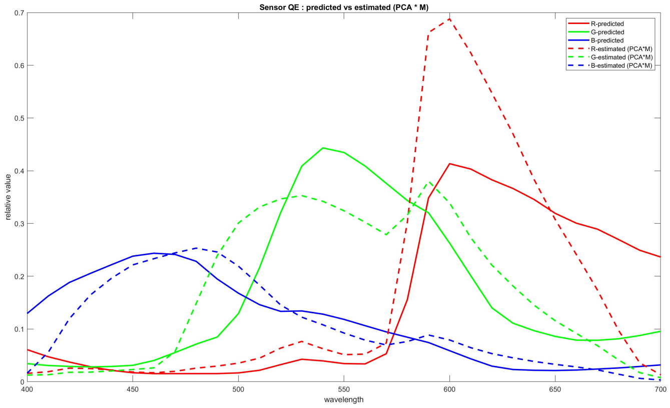
Using a similar approach to method 1, we can approximate a positive 3x3 correction matrix to further improve the QE estimation and response results by minimizing the least square error between the simulated sensor RGB response and the estimated RGB response using the PCA method under illuminant-A subject to a non-negativity constraint. The fit matrix is given by

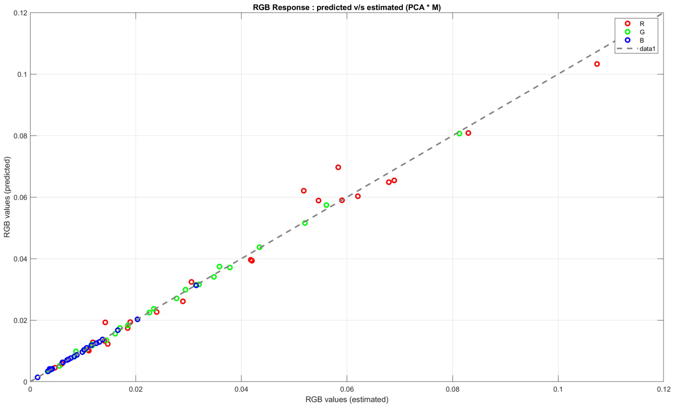


1.000	0	0
0.306	0.575	0.000
0.061	0.095	0.524

From the matrix values, you can observe that there is one significant value of 0.306 that represents the crosstalk between the red and green color channels in the G response.

The estimated sensor QE curves and RGB response plot accounting for this additional positive 3x3 matrix are as follows



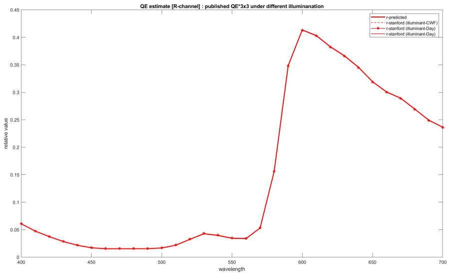


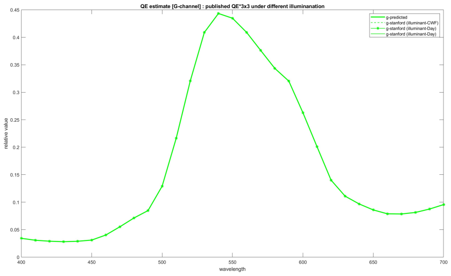
The results above show significant improvement in the estimation results after applying 3x3 correction matrix to PCA algorithm results. We can observe that the blue and green color channel estimates are very close to the sensor QE in comparison to the red color channel estimate. This mismatch in the red channel QE estimation is due to the additional infrared cut-off filter response present in the mobile cameras. This change (sharp drop) in the red channel response due to the IR filter is not accounted for in the QE curves published by the sensor manufacturer resulting in this estimation error.

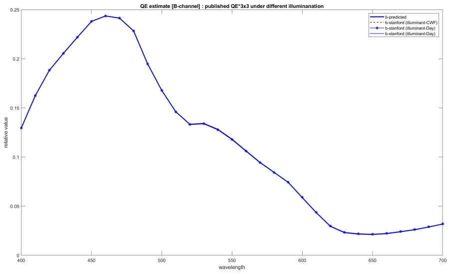
RESULTS UNDER ADDITIONAL ILLUMINANTS

To confirm the results from the above two methodologies are consistent across different illuminants, we validated these approaches under two additional illuminants [Cool White Fluorescent (CWF), Daylight (Day)].

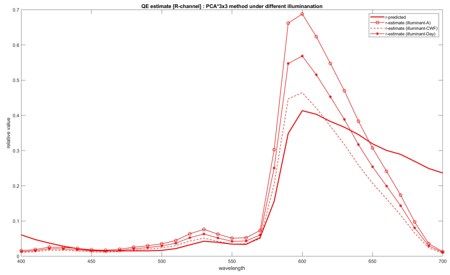
- **Estimated Sensor QE curves under different illuminants**
  Method-1 + 3x3 correction

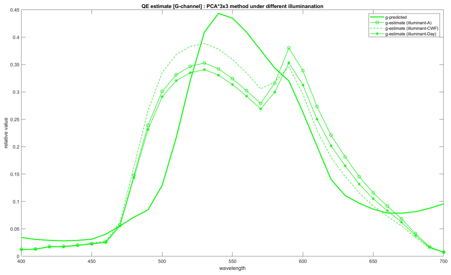


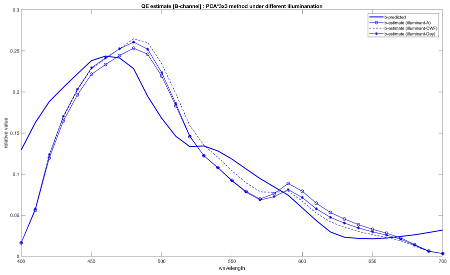




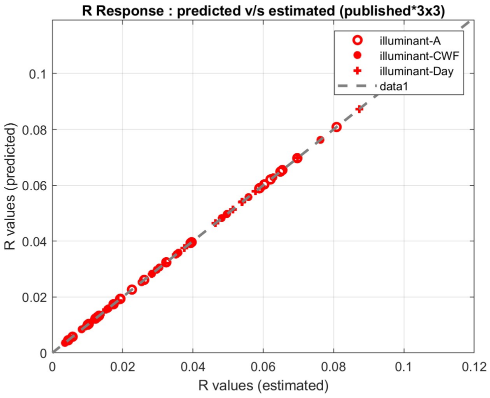
Method-2 + 3x3 correction

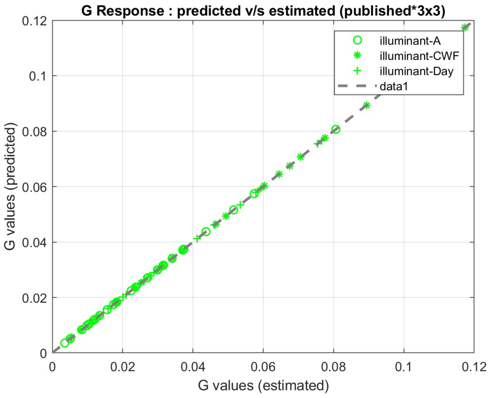


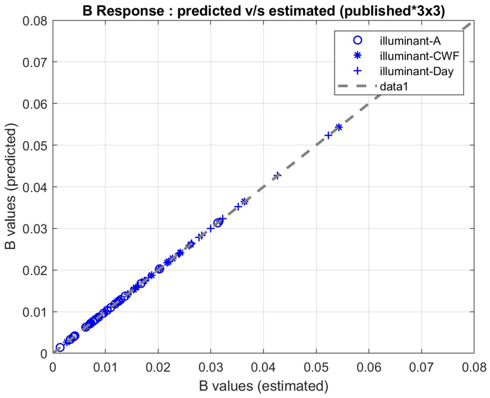




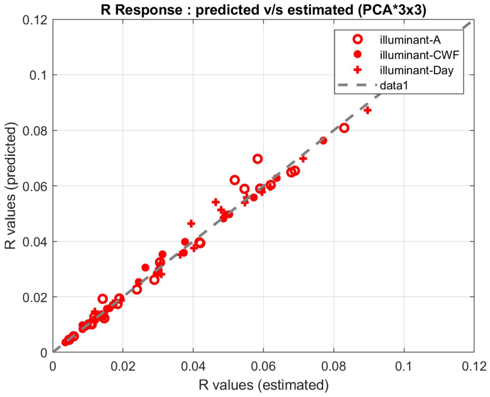
- **Estimated sensor RGB response vs Predicted sensor RGB response**
  Method-1 + 3x3 correction

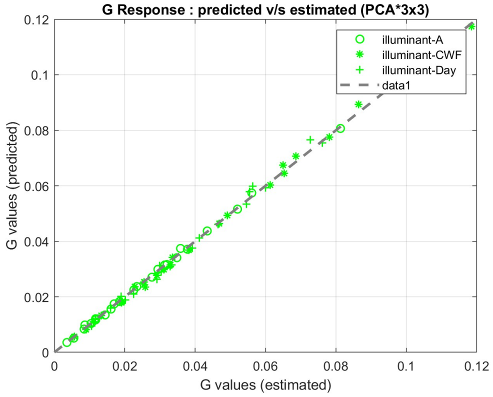


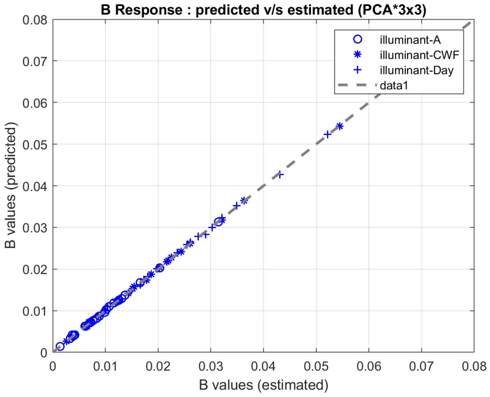




Method-2 + 3x3 correction







From the results, we can conclude that both estimation methodologies perform well under different illumination conditions. As mentioned in the previous section, the underperformance in the red channel QE estimation with PCA method is due to the additional infrared cut-off filter response present in the mobile camera database QE response which is not accounted for in the sensor published QE.

CONCLUSION

In summary, from working on this project, we learned about the sensor QE estimation methods, successfully reproduced the published results from two recently published papers, and further improved the estimation results of the PCA algorithm method. Our experiment results showed that both these methodologies give stable and accurate QE estimation results and do not require any additional expensive, time-consuming process.

However, for deciding which method to choose, we propose the following strategy

- When no additional information about the camera sensor is available, resorting to the Principal Component Analysis based estimation method followed by a positive 3x3 correction would give the best estimation results.
- However, when we have a piece of additional information about the sensor, we should start with the published sensor QE basis with an additional positive 3x3 correction for the most accurate estimation results.

This strategy is in accordance with standard probability theory that with no prior information, the average works as a good strategy. And, on the availability of additional information, using this prior is a better approach.

References

Zheng Lyu, Thomas Goossens, Brian A. Wandell, and Joyce Farrell, *Validation of Physics-Based Image Systems Simulation With 3-D Scenes*, https://stanford.edu/~wandell/data/papers//2022-CornellBoxValidation-Lyu.pdf (Aug 22, 2022)

Shoji Tominaga, Shogo Nishi, Ryo Ohtera, *Measurement and Estimation of Spectral Sensitivity Functions for Mobile Phone Cameras,* https://www.mdpi.com/1198462 (July 22, 2021)

ISETCam - https://github.com/ISET/isetcam

ISETCornellBox - https://github.com/ISET/isetcornellbox

Stanford PSYCH221 slides

Appendix

data

source code (matlab live script)

pre-requisite: add isetcam, isetcornelbox and above data files to matlab search path