# Sensor Calibration and Simulation

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**ABSTRACT**

We describe a method for simulating the output of an image sensor to a broad array of test targets. The method uses a modest set of sensor calibration measurements to define the sensor parameters; these parameters are used by an integrated suite of Matlab software routines that simulate the sensor and create output images. We compare the simulations of specific targets to measured data for several different imaging sensors with very different imaging properties. The simulation captures the essential features of the images created by these different sensors. Finally, we show that by specifying the sensor properties the simulations can predict sensor performance to natural scenes that are difficult to measure with a laboratory apparatus, such as natural scenes with high dynamic range or low light levels.

**Keywords:** Digital camera calibration, characterization, simulation

## 1. INTRODUCTION

Acquiring calibrated test data is a major bottleneck in the design and evaluation of imaging sensors. Using an accurate software simulation of a sensor can simplify the evaluation process, enabling the user to predict sensor performance over a wide range of conditions that cannot be easily or efficiently measured in the lab. Furthermore, accurate simulations can guide the development of sensor components by determining which design changes will meet customers' expectations of image quality. Accurate simulations guide development without incurring the cost of building a new module.

In this paper, we describe the software simulations of three different imaging sensors. The simulation parameters are derived from a few fundamental measurements that characterize sensor spectral sensitivity and electrical properties including dark current, read noise, dark signal non-uniformity and photoreceptor non-uniformity. While we estimate these parameters from a modest set of calibration measurements, we note that these sensor parameters are often provided by the sensor manufacturer in the form of a product data sheet.

We demonstrate the simulation methodology using an integrated suite of Matlab software routines [1]. We apply the simulations to predict sensor performance for a variety of test images, including the Macbeth ColorChecker. We evaluate the simulation accuracy by comparing simulated and measured sensor images to the same target images. We conclude by calculating predicted sensor performance to a variety of scenes that are difficult to measure in the laboratory, including dimly illuminated natural scenes.

## 2. CALIBRATION METHODS

We collected calibrated image data from two cameras. First, we measured a Nikon D200 (10.98 Megapixel) CCD digital. We used a calibrated monochromator to measure the spectral sensitivity of the camera, including the effects of the infrared blocking filter and the camera lens [2]. We also captured a set of 190 images of a dark (zero intensity) field taken with exposure durations ranging between 1/8000 and 30 seconds (hereafter referred to as dark frame images), 150 dark frame images with constant exposure (1/8000 sec), and 65 sensor images of a uniform light field captured with exposure durations ranging between 1/8000 and 1/25 seconds (hereafter referred to as light frames). From these images we estimated dark voltage, read noise, dark signal non-uniformity and photoreceptor non-uniformity using the methods described below.

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We also obtained calibration data from a manufacturer of a 3.1 Megapixel CMOS imaging sensor, hereafter referred to as the Vendor sensor. The manufacturer provided 8 dark frame images with constant exposure duration (10 msec), 10 dark frame images with exposures ranging from 1 msec to 300 msec, and 10 light frame images over the same range of exposures.

*Dark voltage* was analyzed using the set of images of a dark (zero intensity) field taken with different exposure durations (dark frame images). The rate of increase in pixel digital values (DV) over time is the result of dark current. We estimated dark voltage by the slope of DV/time, converted to voltage by the voltage swing and quantization levels.

*Read noise* is the variance in digital values from repeated reads of the same pixel. We derived this variance from multiple measurements obtained in the dark and with the same exposure duration.

*Dark signal non-uniformity (DSNU)* is the standard deviation of the mean pixel value across an array of pixels. DSNU was estimated by averaging multiple measurements in the dark with constant exposure duration. By averaging over multiple measurements, we minimized the read noise. We then calculated the variance in the mean level across pixels to estimate dark signal non-uniformity.

*Photoreceptor non-uniformity (PRNU)* was estimated by analyzing sensor images of a uniform light field captured with different exposure durations. We measured the increase in mean digital value as exposure duration increases. By inspection, we excluded sensor images that are dominated by noise at short durations or saturated at long exposure durations. We found the linear rate of increase of with exposure duration for each pixel. PRNU is the variance in slope across different pixels. The slope differs across the color pixels because they each have different light sensitivity. The variance of the slope, measured as a proportion of the mean slope, is the same across the colored pixels.

We obtained additional sensor information for the D200 camera from several different sources, including published data sheets [3]. For example, we used published data about pixel size, voltage swing [3], well capacity [3, 4], conversion gain [4] and analog gain [4]. Since conversion gain (volts/electrons) is equal to the voltage swing (volts) divided by well capacity (electrons), we could check that these numbers are consistent. The sensor measurements and parameter data was obtained for the Nikon camera when the ISO setting was 100. We also used a 50 mm lens with f-number set to 8.

The Vendor manufacturer also provided measurements of the sensor's spectral sensitivities (including the IR blocking filter), well capacity, voltage swing, pixel size, conversion gain, lens f-number and focal length.

Figure 1 shows the measured spectral efficiencies of the three channels in the D200 sensor. The spectral sensitivity of the Vendor sensor is confidential, as are data about conversion gain, voltage swing, analog gain and well capacity. All other sensor parameters are listed in Table 1.

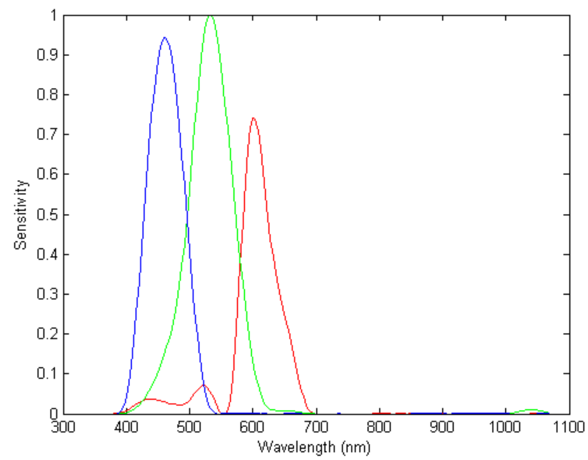


**Figure 1.** Spectral sensitivity of the D200 sensor.

**Table 1: Sensor parameters for ISET simulations**

| **Sensor** | **Vendor** | **D200** |
|---|---|---|
| Pixel width (μm) | 2.2 | 6.05 |
| Pixel height (μm) | 2.2 | 6.05 |
| Fill factor | confidential | 0.9 |
| CFA pattern | gbrg | rggb |
| Dark voltage (V) | 0.0 | 0.0 |
| Read noise (mv) | 4.58 | 0.52 |
| DSNU (mv) | 6 | 0.55 |
| PRNU (%) | 1.7 | 1.126 |
| Conversion Gain (μV/e) | confidential | 30 |
| Voltage swing (V) | confidential | 1.08 |
| Analog gain | confidential | 7.98 |
| Exposure duration (s) | 0.066 | 1/3 |
| Scene luminance (cd/m$^2$) | 5, 15, 40 | 40 |
| Lens f-number | 2.8 | 8 |
| Lens focal length (mm) | 4.88 | 50 |
| Well capacity (electrons) | confidential | 36000 |

## 3. SIMULATIONS

We used the ISET Matlab software routines to integrate the calibration data (see Table One) and predict the sensor response to a variety of test targets, including the Macbeth ColorChecker under tungsten illumination. We then compared the predicted sensor image array to the actual sensor array created when the imaging sensors captured an image of the same scene.

The ISET simulations begin with a representation of scene spectral radiance (photons/sec/nm/sr/m$^2$). We used a multispectral imaging system [2] to measure the spectral radiance and scene luminance of the Macbeth ColorChecker under tungsten illumination; this was the actual scene that was captured by the Nikon D200 camera. We estimated the mean scene luminance by averaging the luminance for each of the 24 patches on the Macbeth ColorChecker under the tungsten illumination.

The Vendor camera also captured an image of the Macbeth ColorChecker illuminated with tungsten light. We used the multispectral scene data as an approximation to that scene as well. The sensor manufacturer provided illuminance measurements taken at the location of the Macbeth ColorChecker. Using measurements in our own lab, we are able to convert their illuminance measurements to mean scene luminance. Since the manufacturer provided raw sensor images of the Macbeth ColorChecker at three different scene luminance levels, we ran ISET simulations for all three images. We report the data for the scene with mean luminance of 15 cd/m$^2$ (100 lux illuminance at the target). The results are comparable for the sensor images as well.

We use ISET to convert the scene radiance image (photons/sec/nm/sr/m$^2$) into an irradiance image (photons/sec/nm/m$^2$) at the sensor. ISET is capable of simulating a full ray trace calculation using lens description data derived from lens design software such as Zemax® or Code V®. Because these data were not available, however, we used a diffraction-limited optics model to calculate wavelength-dependent optical transfer functions based on the finite aperture as determined by the f-number of the taking lens. Hence, the quality of the spatial images is better than one would predict with a conventional lens with some aberration.

Finally, we use ISET to convert the sensor irradiance image into electron counts within each pixel of the image sensor. ISET models the imaging sensor as a linear device with specific spectral quantum efficiency. The pixel model includes several noise sources. The sensor model accounts for variation between pixels in both their offset and gain.

The only unknown parameter in these simulations is the pixel fill factor. For each sensor, we varied pixel fill factor to get the best fit between measured and simulated sensor RGB values. The best-fitting fill factor was 90% for the Nikon CCD sensor and 50% for the Vendor CMOS sensor. These are consistent with conventional sensor fill-factors.

## 4. RESULTS

Figure 2 compares the predicted and simulated sensor images of the Macbeth ColorChecker after it is demosaiced using bilinear interpolation. These processed images (demosaiced but not color-balanced) illustrate visually the similarity between the measured and simulated sensor images.

D200 Sensor | Vendor Sensor

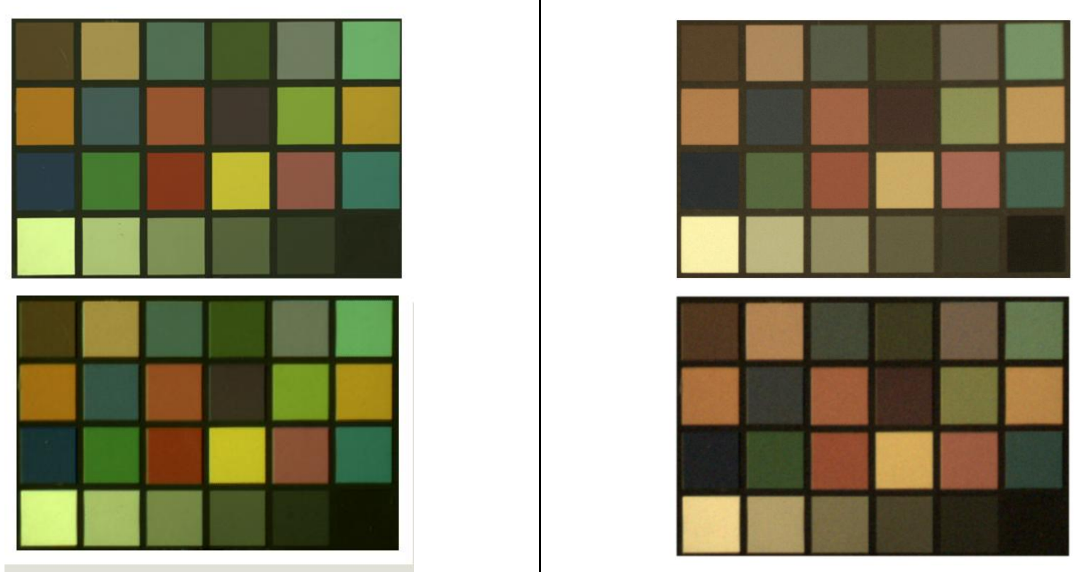

**Figure 2**: Measured (top) and simulated (bottom) sensor images after bilinear demosaicing. Parameters of the ISET simulations are listed in Table 1. The mean luminance of the scene captured by the D200 sensor was 40 cd/m$^2$ and the exposure duration was 333ms. The mean luminance of the scene captured by the Vendor sensor was 15 cd/m$^2$ and the exposure duration was 66 ms.

To compare the simulated and measured sensor images quantitatively we calculate the mean and standard deviation of the sensor RGB values for each of the 24 patches in the Macbeth ColorChecker. We use the mean divided by the standard deviation of sensor values as an estimate of the signal-to-noise ratio (SNR).

The left column of Figures 3 and 4 plot the mean of the measured RGB values against the mean of the predicted RGB values for the D200 and Vendor sensors. The right hand column of Figures 3 and 4 plot the estimated SNR values for the simulated and predicted sensor values. The ISET simulated sensor images are a reasonable approximation to the real sensor images.

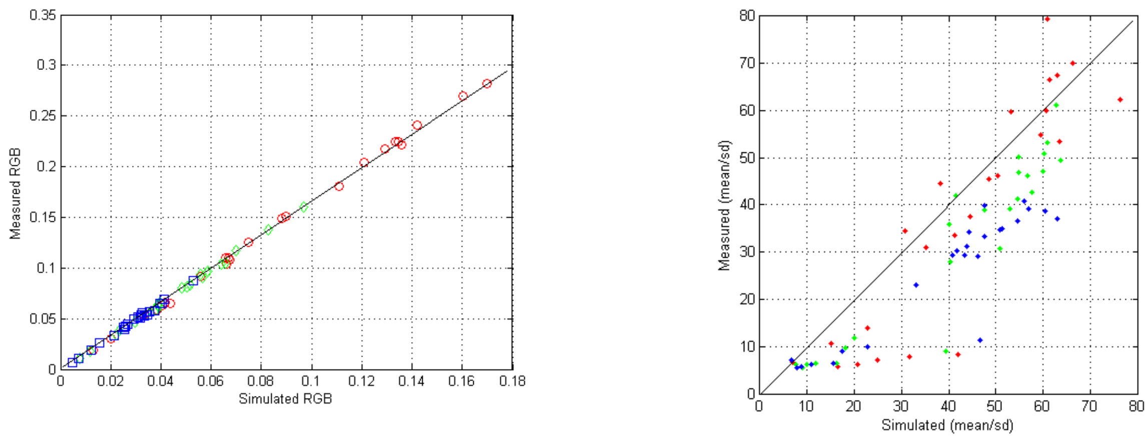


**Figure 3**: The left graph shows the mean of the measured RGB values plotted against the mean of the predicted RGB values in the D200 sensor image of the Macbeth ColorChecker with mean luminance 40 cd/m$^2$. The right graph plots the mean RGB values divided by the standard deviation of the RGB values for each of the 24 patches in the Macbeth ColorChecker.

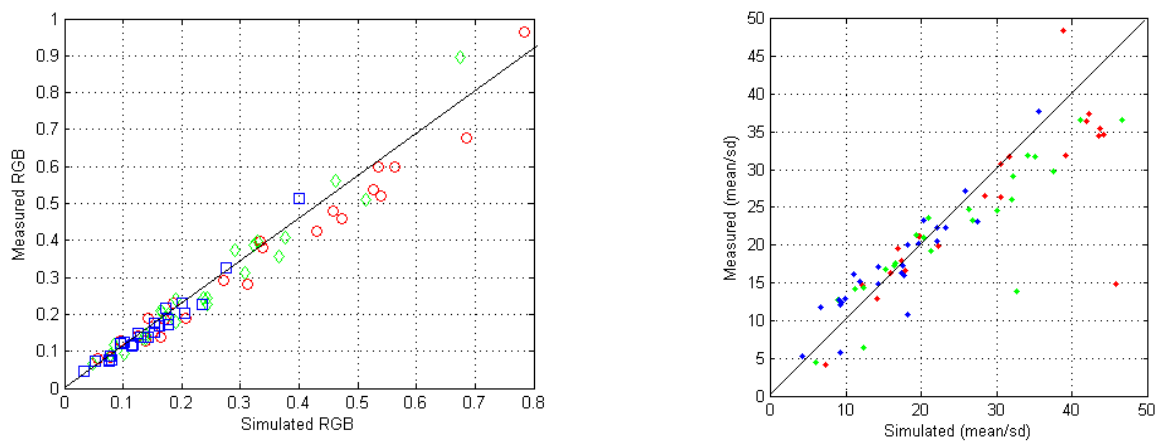


**Figure 4**: Measurements using the Vendor sensor with a Macbeth Color Checker at 15 cd/m$^2$ mean luminance. Other aspects as in Fig. 3.

We can compare the color accuracy of the simulated and measured sensors. For both simulated and real sensor images, we find the 3x3 matrix that transforms the RGB sensor values for each of the 24 patches in the Macbeth ColorChecker into the XYZ values for the patches under D65 illumination [5].

Figure 5 shows a histogram of the ΔE color differences between the desired XYZ values and the XYZ values generated by the optimal 3x3 transform matrix. The left column of each figure shows results based on the measured sensor image and the right hand column shows results based on the simulated sensor image. Color accuracy, as measured by the ΔE color difference metric, is comparable for both measured and simulated sensor images.

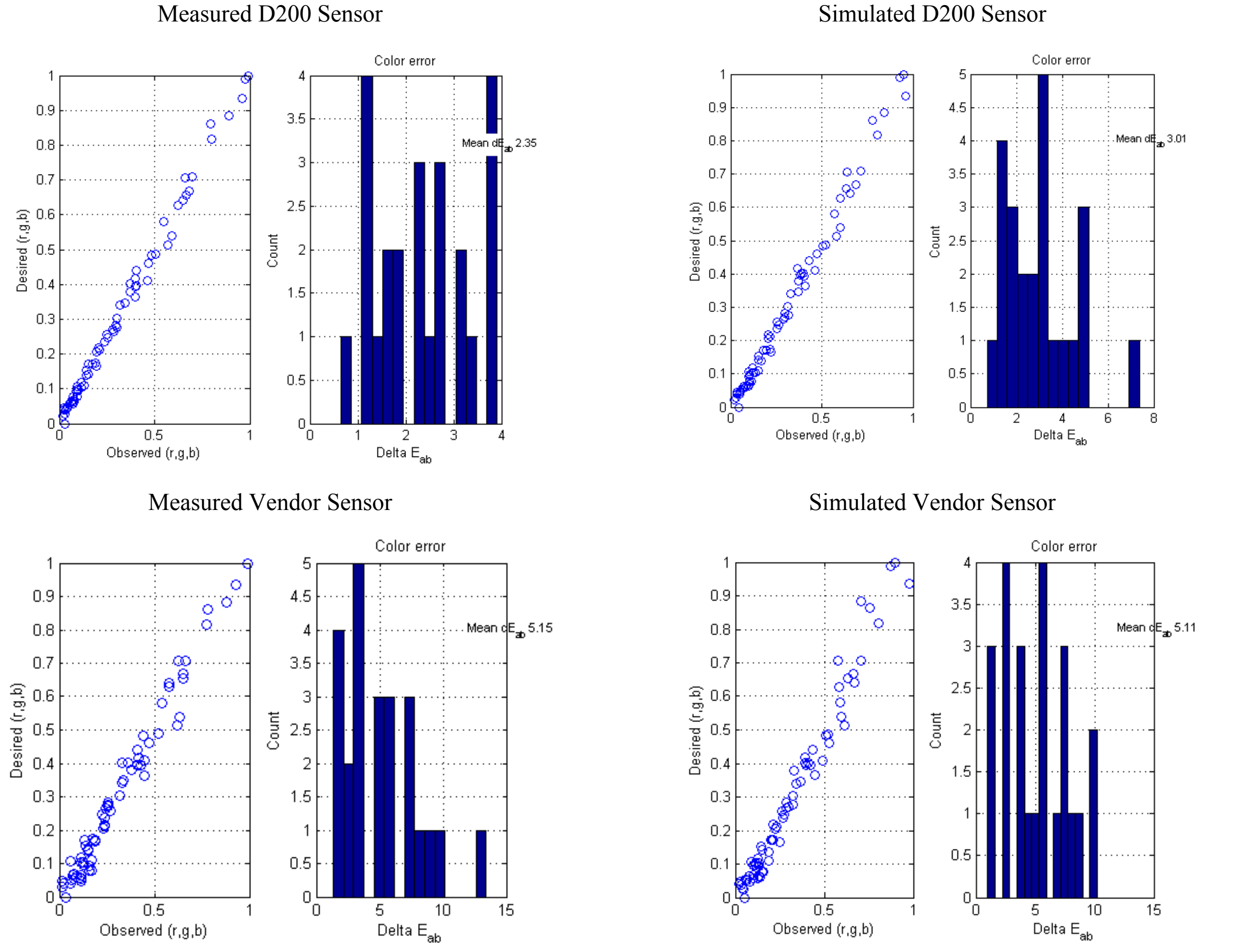


**Figure 5.** Histogram of the ΔE color differences between the desired XYZ values and the XYZ values generated by the optimal 3x3 transform matrix. The left figure shows results based on the measured sensor image and the right figure shows results based on the simulated sensor image.

## 5. APPLICATIONS

In the previous section, we show that it is possible to predict performance for two very different sensors given information about the scene radiance, lens properties and sensor parameters. In this section we use the ISET simulations to predict sensor performance for a variety of scenes that are difficult to measure, including low light level natural scenes.

Figure 6 illustrates how the two sensors would perform on a dimly illuminated face. The scene was created using multispectral scene data [2] and the spectral power distribution of tungsten light. The mean scene luminance was 5 $cd/m^2$ and the exposure duration was 66 milliseconds for both sensors. The sensor images were demosaiced with bilinear interpolation and color-balanced using the Gray World algorithm.

The lower panel of Figure 6 plots sensor SNR as a function of voltage, and shows the separate contributions that read noise, DSNU, PRNU and light level (photon or shot noise) have on the total sensor SNR[i]. This analysis shows that the quality of the image captured by the Vendor sensor is determined by read noise and DSNU for nearly all voltage levels. The quality of the image captured by the Nikon D200, however, is determined by read noise and DSNU only at very low voltages. As voltage level increases, the quality of the Nikon D200 image is determined by shot noise and PRNU.

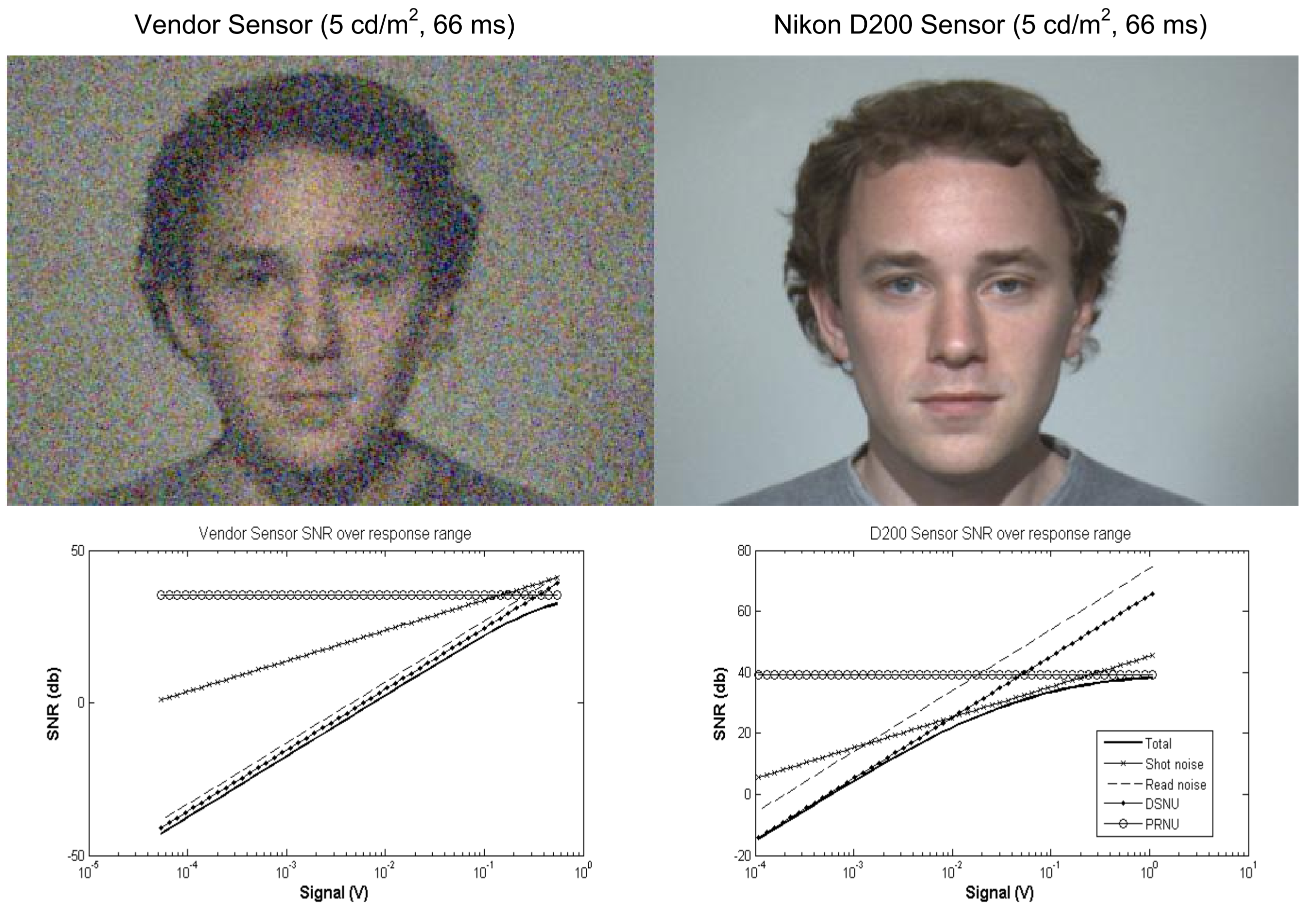


**Figure 6.** ***Top Panel*****:** Simulated images captured by the Vendor sensor (top left) and the D200 sensor (top right) of a dimly illuminated face. The mean scene luminance 5 cd/m$^2$ and the exposure duration was 66 milliseconds for both sensors. The sensor images were demosaiced with bilinear interpolation and color-balanced using the Gray World algorithm.
***Bottom Panel***: Sensor SNR(black) plotted as a function of voltage for the Vendor sensor (bottom left) and the D200 sensor (bottom right). Individual contributions of read noise , DSNU, PRNU and shot noise are also shown.

When sensor performance is determined more by DSNU and read noise than by shot noise or PRNU, increasing pixel size will have an insignificant effect on image quality. This can be illustrated by comparing two Vendor sensors that have comparable noise characteristics, but differ in pixel size. Figure 7 shows the images captured by sensors with 1.4 micron pixels (left hand side) and 2.2 micron pixels (right side). The original scene has a mean luminance of 5 cd/m$^2$ and the exposure durations are 66 milliseconds, as in the previous example. Unfortunately, the well capacity, conversion gain and pixel fill factor cannot be reported here. But these data were provided to us by the two different sensor vendors.

As Figure 7 demonstrates, the different between the pixel size in the two sensors has a negligible effect on image quality, compared to the effects of read noise and DSNU. The lower panel of Figure 7 shows what the image would look like if read noise and DSNU are removed. In this example, the image captured by the sensor with 1.4 micron pixels is slightly noisier than the image captured with 2.2 micron pixels, as would be expected.

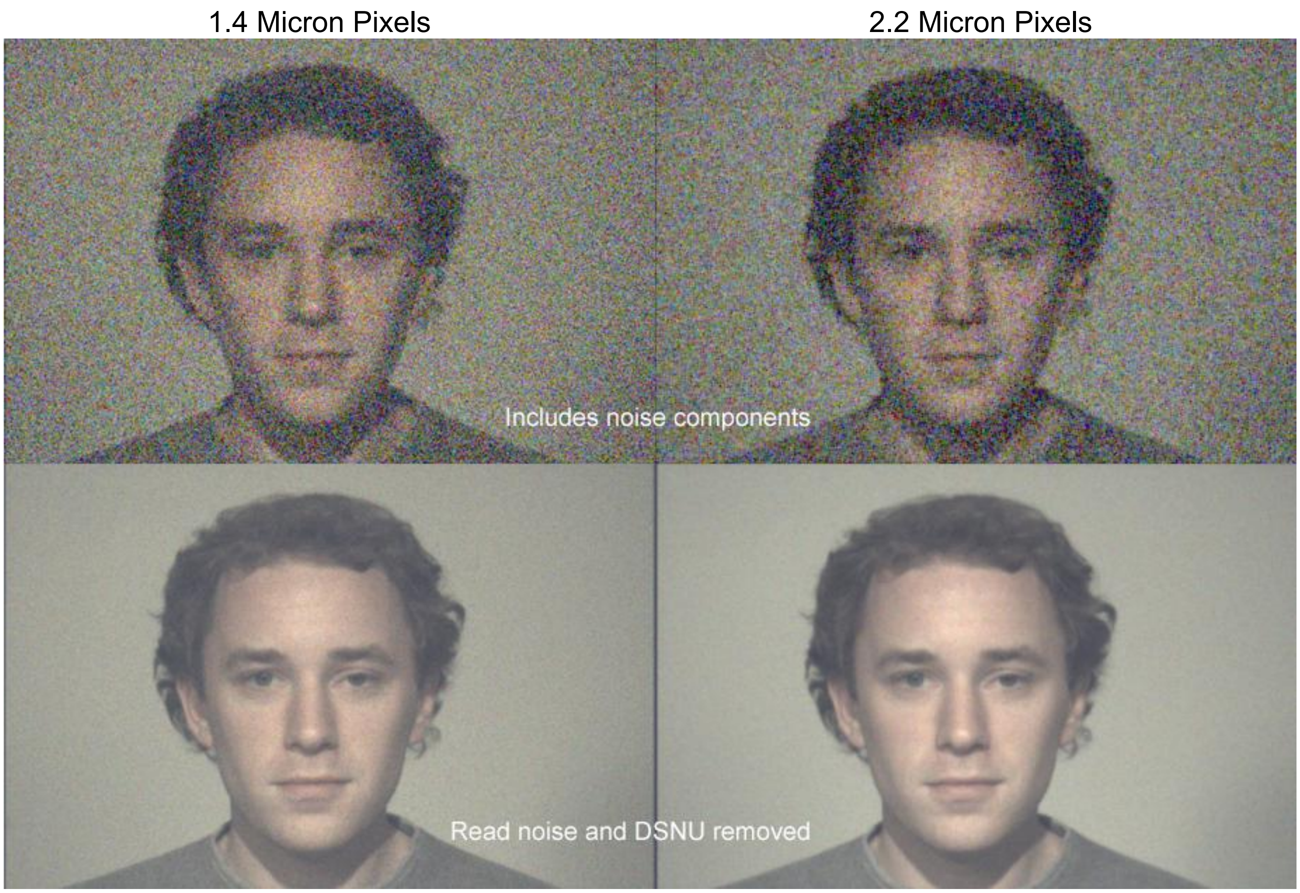


**Figure 7.** Images captures by sensors with 1.4 micron pixels (left hand side) and 2.2 micron pixels (right side) of a face illuminated with tungsten light. The mean scene luminance was 5 cd/m$^2$ and the exposure durations were 66 ms. The top images show images from the sensors with simulated noise properties, the bottom images show images from the same sensors with read noise and DSNU removed.

## 6. CONCLUSIONS

In this paper we demonstrate the process of developing simulation models for several different imaging sensors and illustrate the applications of these models. Calibration data were acquired from two very different imaging sensors, a 3.1 Megapixel CMOS sensor and a 10.98 Megapixel CCD sensor. The data needed to characterize the sensors (Table 1) can be obtained from a a few images in a test environment, or from manufacturers' information. With this information, the simulations provide a good approximation to the performance of the different sensors. The accuracy of the ISET approximations is shown in Figures 2-5.

As the data and simulations illustrate, performance differs greatly between sensors. Considerable experimental effort is required to develop a sensor into a working prototype; the process can be time-consuming and inefficient. Further, it is difficult to create good examples of natural scenes that test sensor performance. Properly validated simulation methods could make it realistic to save time during the sensor evaluation process. Calibrated spectral scene images offer a simple way to create challenging natural inputs to evaluate the simulated sensor.

Once we have confidence in the simulations, it is further possible to estimate how the sensor will perform when acquiring scenes that are difficult to recreate or calibrate (high dynamic range, low light levels, and so forth) in the laboratory (Fig. 8) or with a variety of imaging optics. It is also possible to evaluate the effects that different sensor components have on image quality, as well as different post-processing algorithms. In principle, then, different laboratories can communicate about a sensor by simply sending the data files that characterize the sensor to one another. The simulator could be used to verify the properties of a particular sensor in different imaging conditions or when coupled with different types of lenses.

Continuing validation of the simulation technology and methods for estimating the sensor characteristics should lead to high efficiencies for sensor evaluation. Ultimately, as we gain increasing confidence in the simulation, it can be used to design novel sensor designs as part of the manufacturing process.

## 7. ACKNOWLEDGEMENTS

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[i] SNR was calculated by 10*log10(S/N) where S =Volts/Conversion Gain)$^2$ and N is the sum of the variance of shot noise, read noise, dsnu and prnu.