Figures of Merit for True-Color Image-Intensified Cameras

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ABSTRACT

Figures of Merit (FOMs) are presented that quantify the relative range, color-based contrast, and color fidelity of color image intensified (night vision) systems. These FOMs allow for objective comparisons of differing color camera systems and are particularly useful for designing and optimizing True-Color Image-Intensified (TC-I2) cameras and associated color mixing and image processing algorithms. A system model in conjunction with the FOMs can be used to assess color and overall performance before actually investing in building hardware. For instance, the FOMs can be used to assess system performance when selecting components with spectral sensitivity such as color filters, the photocathode, or CCD/CMOS/EMCCD detectors. In addition to allowing for the comparison of different color images, the FOMs also allow for an objective performance comparison between color and monochrome I2 systems by accounting for both the reduced signal level and increased contrast that is associated with true-color imagery.

The FOMs can be applied to spectral databases, simulated images, or images captured with different low light level cameras. For broad characterization of systems, techniques are demonstrated for application of the FOMs to simulations of a standardized color chart and a general spectral database. For more specific characterization, the FOMs can be applied to camera responses for specific target/background combinations.

1. INTRODUCTION

Studies using human subjects are the ultimate test of imaging systems; however, such studies are subjective, costly, and difficult to integrate into hardware design analyses. For this reason, objective figures of merit (FOMs), such as the minimum resolvable contrast (MRC) [1,2] have been developed over the years for the assessment of night vision systems (specifically image-intensified goggles and cameras). However, these calculations typically assume a monochrome image, and the additional information content and contrast that is available with color imagery is not considered. Alternatively, standard FOMs developed by the color-imaging field do not consider comparisons of color to monochrome images, and furthermore are not well suited for assessing image-intensified cameras since they do not consider the conditions of low-light-level imaging.

The FOMs presented here are specifically designed for characterizing true-color image-intensified cameras. In addition, these FOMs can also be applied to (i) monochrome images (ii) false-color images generated by fusion of I2 and thermal IR imagery, or (iii) pseudo color generated from brightness color slicing. The FOMs can be used on simulated responses, simulated images, or actual images captured with different types of cameras.

For brevity, in this paper we focus on applying the FOMs to simulated responses for different color filter sets in front of a visible to near-infrared (V-NIR) image intensified camera. The responses are calculated for a standardized color chart and a spectral database of common objects.

1.1. True-Color Image-Intensified Cameras

Color improves the information content of images in two ways. The first is that color improves contrast, which allows for better scene segmentation and object detection, particularly in the case of noise degraded images. Numerous DoD studies have shown that scene understanding, reaction time, and object recognition with color images is significantly faster and more accurate than with monochrome imagery [3,4], see Table 1. This contrast improvement can apply to both true-color and false-color images, where the latter can be formed by the fusion of different types of sensors. The second way color improves information content is by allowing for the use of stored color knowledge in the brain or computer database; this additional information can enable better object recognition and scene understanding. This second improvement would only apply to true-color images, since false-color images do not necessarily match the stored color, and may in fact be detrimental in this regard.

Table 1. Measurement of Error rates in identification tasks for different levels of noise and different color composition. Adapted from Reference [3] page 59.

Noise Level	Error Rate of Identification			
	True-Color	True-Monochrome	False-Color	False-Monochrome
0	0.4%	1.2%	0.6%	2.2%
1	1.6%	3.0%	3.2%	4.0%
2	3.0%	8.1%	8.3%	10.5%

To obtain true-color images there must be a mechanism to filter or split the different parts of the visible spectrum so that color information can be extracted. Assuming a single light collection device, this need to filter the input has the consequence of reducing the available signal. This reduction in signal is the primary drawback to a true-color image intensified (TC-I2) system. Furthermore, monochrome image-intensified systems are typically designed to take advantage of the relatively high signal of night sky radiation in the NIR, and to mitigate the inherent reduction in signal due to filtering, a true-color system must also be able to utilize this NIR light (sensitivity to NIR is also needed for viewing of NIR laser aiming devices.)

In developing FOMs for TC-I2 cameras we were driven by the desire to quantify the trade-off between contrast and signal and also establish a methodology to determine the color reproduction ability of a system that utilizes the full V-NIR spectral content of the night sky.

1.2. Color Science

Colorimetry is a multifaceted discipline that combines psychology, physiology, physics, and engineering. In our case, the complexity is compounded by our desire to utilize NIR radiation along with visible color. In this section, we give a brief description of some of the color science terms and techniques used in the paper.

1.2.1. CIE Definitions

For color processing and analysis we rely on definitions from the International Commission on Illumination (CIE) [5]. Many of these definitions are based on the CIE tri-stimulus values XYZ that approximate the photopic (daylight color vision) spectral response of the human eye. One definition of the XYZ response is shown in Figure 1. In this graph the horizontal axis extends to the NIR region of the spectrum to demonstrate the relatively large portion of the spectrum that is typically irrelevant in color science, but is in fact relevant to I2 imaging.

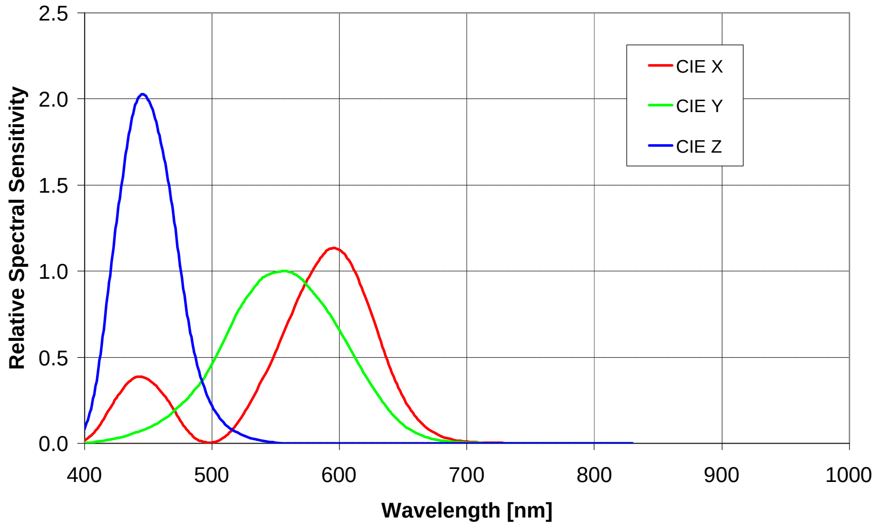


Figure 1. CIE XYZ matching functions used to model the response of the human color vision.

For contrast analysis (discussed in Section 2.1) we use the currently CIE recognized standard for calculating color difference. The quantity is known as Delta E 2000 (ΔE_{2000}), and is given by equation 1 [6],

$$\Delta E_{2000} = \left[\left(\frac{\Delta L}{S_L} \right)^2 + \left(\frac{\Delta Ch}{S_C} \right)^2 + \left(\frac{\Delta H}{S_H} \right)^2 \right]^{1/2} . \tag{1}$$

Here, L approximates the Lightness response of human vision, and is used to quantify the brightness of an image; Ch is the Chroma and H is the Hue, which are both used to quantify the color response of human vision. The quantities S_L, S_C, and S_H are weighting functions that adjust the calculated difference depending on the colors' locations in the standard CIE color space. As compared to simplified formulas without weighting functions, ΔE_{2000} has been shown to be superior at capturing human perceived color and lightness differences [7].

1.2.2. Color Space

There are many different color spaces to consider when generating color displays with a set of color filters. There is the display space described by the (R,G,B) vector for each pixel; there is the human response (X,Y,Z) discussed above; and there is the space defined by the filters, which we take to be (F_1,F_2, ..F_k), with k representing the number of filters that are used in the scene capture. A transformation matrix can describe linear transforms from one space to another, such as

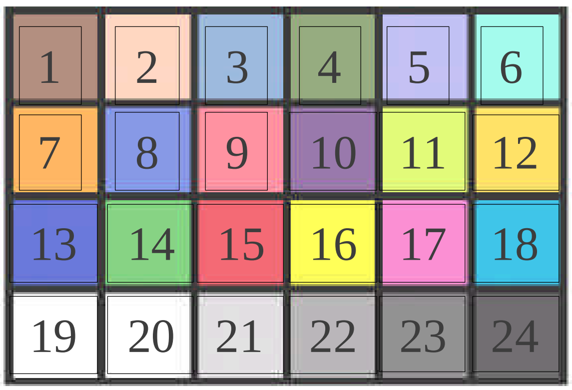
$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \left(\quad \mathbf{T} \quad \right) \times \begin{bmatrix} F_1 \\ \vdots \\ F_k \end{bmatrix}. \tag{2}$$

In this equation, **T** is the 3×k transformation matrix that converts the filters' color space into the display RGB values. The transformation matrix can vary as a function of lighting conditions to provide the proper color balance. Non-linear effects, such as "gamma" scaling that are used to account for the non-linear response of the eye or non-linear output of a display device can be applied either before or after application of the linear transformation matrix.

For purposes of assessing color reproduction, one must assume an RGB color space for display. We use the sRGB color space, this color space uses the CIE designated D65 illuminant, "natural daylight" and a Gamma = 2.2. For our purposes, the use of this color space means that we are comparing color reproductions to color references as they should appear to a human in natural daylight.

1.2.3. Macbeth Chart

For testing, characterizing, and calibration we use the GretagMacbeth ColorChecker chart (herein referred to as the Macbeth chart). This chart consists of 24 scientifically prepared color squares with spectral reflectances that mimic a wide range of colors and shades. A computer reproduction of the chart is shown in Figure 2, along with the associated names of each square.



1. Dark Skin	9. Moderate Red	17. Magenta
2. Light Skin	10. Purple	18. Cyan
3. Blue Sky	11. Yellow Green	19. White
4. Foliage	12. Orange Yellow	20. Neutral 8
5. Blue Flower	13. Blue	21. Neutral 6.5
6. Bluish Green	14. Green	22. Neutral 5
7. Orange	15. Red	23. Neutral 3.5
8. Purplish Blue	16. Yellow	24. Black

Figure 2. Macbeth Color Chart shown with associated names for each color square.

In addition to reference XYZ values from the manufacturer, there are many additional sources of data on this chart, including, spectral reflectance measurements, expected RGB values in various color spaces, and *L*,*Ch*,*H* values for each square [8,9].

1.2.4. Spectral Database

The Macbeth chart is an excellent laboratory tool. However, since there are not many DoD applications that require a user to discern different squares on a Macbeth chart, tests using more realistic targets are needed. Without initially relying on expensive field tests, one can use a spectral database consisting of the spectral reflectance signatures of relevant target and background materials to perform such tests.

The need for an alternative to the Macbeth chart is particularly important for our purposes since the Macbeth chart is designed for the characterization of color devices operating in the visible spectrum only and does not provide any useful data in the NIR. For example, live vegetation has a relatively large reflectance in the NIR, which is not represented by the "Foliage" square in the Macbeth chart.

For the tests presented here we compiled a collection of spectral profiles of 12 different objects, herein referred to as the “Spectral Database” shown in Figure 3. The spectra for “Grass”, “Dry Grass”, “Brown Clay”, “Concrete”, and “Olive Green Paint” were taken from the ASTER spectral library maintained by JPL [11], the other spectra were collected at OKSI using an Ocean Optics model USB2000 hand-held VIS-NIR spectrometer with Spectralon® as a white reference.

By applying the XYZ spectral matching functions, RGB values can be calculated that approximate the appearance of the objects in the Spectral Database. Results of such calculations are shown in Figure 4 for the sRGB color space, (i.e., using illuminant D65 and Gamma = 2.2).

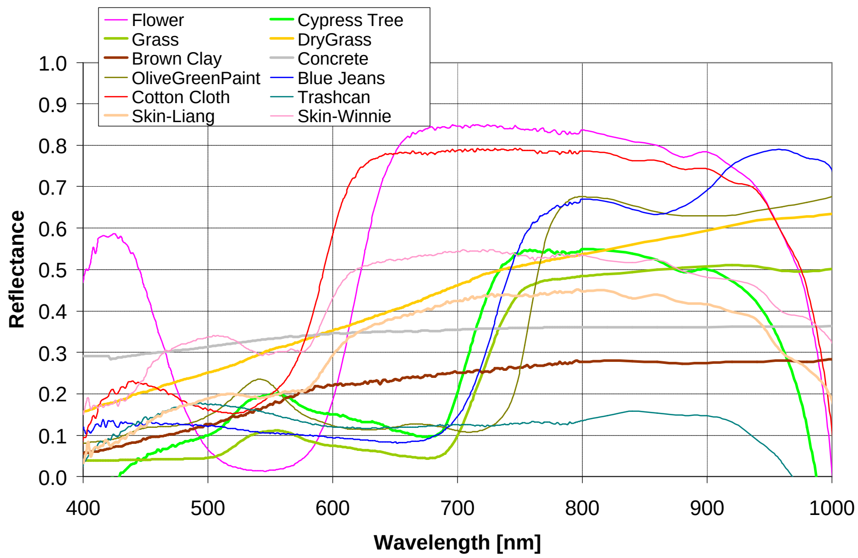


Figure 3. Spectral database used for analysis.

Purple Flower	Cypress Tree	Grass	Dry Grass	Brown Clay	Concrete
Olive Green Paint	Blue Jeans	Pink Shop Rag	Trashcan	Skin-Liang	Skin-Winnie

Figure 4. Examples of colors as would be perceived in "natural daylight" for items in the Spectral Database.

2. FIGURES OF MERIT

The main goals in devising FOMs for the characterization of TC-I2 cameras are two fold: (1) to enable objective comparisons between color and monochrome systems, and (2) to assess the performance of different camera components and image processing routines, in particular allowing for the testing of different filter designs and color transformations.

2.1. Contrast

For monochrome imaging systems the contrast between two portions of an image is simply related to the difference in the signal level. For a color image the calculation is more complicated, particularly if one wants to assess the human perceived contrast. In addition, for our purposes we require a contrast metric that can be meaningfully applied to both color and monochrome images. The quantity ΔE_{2000} given by Equation (1) ideally meets the above requirements. The greater the value of ΔE_{2000} for two portions of the image, the greater the contrast and the more easily distinguishable are the two items. The maximum value of ΔE_{2000} is 100, which occurs for the comparison of pure black to pure white. We find it convenient to rescale this value so that it ranges from 0 to 1, and thus our contrast metric is defined as:

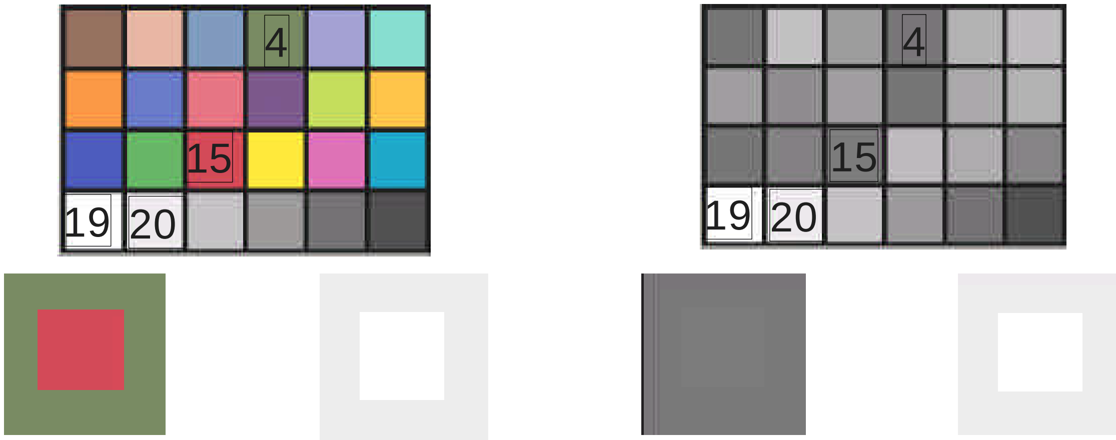
$$\text{Contrast:} \quad C \equiv \frac{\Delta E_{2000}}{100} . \tag{3}$$

Contrast calculations that simply use RGB values or even XYZ values [10] have limited utility since these color spaces are far from being perceptually uniform. For example, two different pairs of colors may give the same contrast values in this color space, while to the eye the contrasts are perceived to be very different. On the other hand, the quantity ΔE_{2000} is designed specifically so that when a pair of colors give a certain value of ΔE_{2000}, the contrast of those two colors is perceived by the eye to be the same no matter what two colors were used in the calculation. Thus, ΔE_{2000} equally describes the contrast for grey levels (monochrome) as for colors.

The value of $\Delta E_{2000} = 1$ ($C = 0.01$) is intended to represent a "just noticeable difference" between two colors regardless of their location in color space. In practice, we find that a threshold value of $\Delta E_{2000} = 5$ ($C = 0.05$) is more realistic for being able to distinguish one color from the next in standard images (the more noise in the image the higher this threshold will be). Based on this, we define another metric to designate cases of indistinguishable combinations of colors as being "Below Threshold":

$$\text{Below Threshold:} \quad C < 0.05 \ . \tag{4}$$

Examples of calculated values of C are shown in Figure 5 for two pairs of squares of the Macbeth chart for both color and monochrome images. When comparing color to monochrome, this figure shows that for the "foliage" and "red" squares, color vastly improves the contrast. In fact, the contrast is so low for the monochrome image that the two squares are on the verge of being indiscernible; this is reflected by a "Below Threshold" contrast value. . Figure 5 also shows that contrast difference in color and monochrome is essentially the same for the "white" and "neutral 8" squares, as expected.



C = 0.46 for 15 & 4 C = 0.10 for 19 & 20 C = 0.02 for 15 & 4 C = 0.10 for 19 & 20

Figure 5. Top Row: Macbeth chart images in color and monochrome. Bottom Row: comparison of different pairs of squares in the Macbeth chart along with calculated values of *C*.

2.2. Color Error

For surveillance applications, much of the advantage a color imaging system affords a user is through additional contrast. However, having objects and scenery appear in their familiar colors is also useful for object recognition and scene understanding. To quantify the color fidelity of a given system we must compare an image produced by the system to an acceptable standard. This comparison is done objectively by using a modified version of the total contrast described by Equations (1) and (3). For this purpose, the portion of C due to the luminance is left out and only the Chroma (ΔCh) and Hue (ΔH) differences are used,

$$\text{Color Error}: \quad ErrC = \frac{1}{100}\left[\left(\frac{\Delta Ch}{S_C}\right)^2 + \left(\frac{\Delta H}{S_H}\right)^2\right]^{1/2} . \qquad (5)$$

Here, a color error of $ErrC = 0$, means that the color is perfectly reproduced. Since lightness information is not included, this metric is not dependent on brightness scaling and thus different shades of the same color (even different greylevels) should have $ErrC \approx 0$. The Color Error parameter captures the advantage that a true color system has over monochrome or false color systems. It also provides a means of assessing the reproduction capabilities of different filters and different transformation matrices for a variety of targets, lighting conditions, etc.

As mentioned above, the Macbeth chart is used throughout the imaging field for such color reproduction tests. As a result, there are many documented sources of the spectral reflectance and expected color values in many different color spaces. We use the Macbeth chart for color error analysis, but for reasons mentioned above, we also calculate the color error using the spectral database. To obtain expected color coordinates for the objects in the spectral database we simulate the expected human response using the XYZ curves shown in Figure 1 along with the spectral reflectances shown in Figure 3 and the spectral profile of illuminant D65.

2.3. Relative Range

An important metric used to characterize imaging system is the range (or distance) at which an object can be detected, recognized, or identified. Subjective field tests involve human operators attempting to accomplish such vision tasks as discerning bar chart patterns. To enable more efficient objective comparisons, a number of different factors [12,13] such as collection optics, atmospheric conditions, detector noise, target size, etc., have been factored into mathematical expressions that estimate the range. We have devised a Relative Range equation that is based on these basic range equations, but only considers difference in the spectral response of the system. The differences we consider only affect the contrast, *C*, and the signal to noise ratio, *SNR*, of the output image with all other factors in the range equation unchanged. With a survey of range equations we find that, in general, the range is calculated as being linearly proportional to both the contrast and the SNR, as

$$\text{Range}: \quad R \propto C\ SNR\,. \tag{6}$$

By using the contrast presented in Equation (3), we are able to assess the relative range for both color and monochrome systems. For actual color low light level images (taken with different filters, or produced by fusion of different devices), the contrast and the average SNR can be measured by analyzing the images. However, the real utility of such equations comes with assessing different systems in the design phase by analyzing simulated images.

The CCD noise in image-intensified cameras, or the FPA noise in thermal IR systems is often dominated by the shot noise so that the SNR is proportional to the square root of the signal *S*. We therefore can write a simple relative range equation as

$$\text{Relative Range}: \quad R_r \equiv \frac{C_1\sqrt{S_1}}{C_0\sqrt{S_0}}\,, \tag{7}$$

where the indices refer to quantities for two different camera systems that differ only in their spectral sensitivity. Both the contrast and the signal can be predicted for a given system using a spectral simulator, such as that described in Section 3.1.

This Relative Range equation captures the essential tradeoff between a color and monochrome system: contrast versus signal.

2.4. Color Transformation Noise

When used to characterize measured images the SNR can be measured directly. When analyzing simulated images we can assume the raw SNR is simply related to the square-root of the signal, and thus we can use Equation (7). However, Equation (7) does not capture additional speckle noise that can be introduced by the process of applying a transformation matrix to generate a color output (see Equation (2)). This type of noise occurs when different filter states are subtracted from each other to produce a single output color: the larger the values of the transformation matrix coefficients, the greater the speckling. Simply put, when the transformation is used to amplify small differences in the filter states so that colors are more distinguishable, then small differences due to noise will also be amplified and be more noticeable in the display.

We can come up with a simple metric for assessing this noise by assuming that the signals from the different input filter states are equal on average. With this assumption, the transformation noise for each of the RGB output colors depends on the ratio of the sum-square to the sum of the matrix elements T_{ik} in each row. By averaging all 3 output colors together, a single scaling factor can be found that quantifies the additional noise due to the transformation as

$$N_T = \sqrt{\sum \frac{T_{ik}^2}{3}} \Bigg/ \sum \frac{T_{ik}}{3} \quad . \tag{8}$$

Note that for direct transformations that map a single input filter state into a single display color with no scaling factor (e.g., a unitary matrix), then there is no additional noise associated with the transformation and $N_T = 1$.

Additional transformation noise degrades the image and thus the range. Equation (8) can be integrated into the Relative Range equation to reflect this fact. However, we choose to keep it separate for three reasons: (1) the assumption of equal input signals for all filter states is not always appropriate; (2) there are means of drastically reducing this type of noise without adversely affecting the other FOMs; and (3) it is more informative to consider color noise and lightness noise separately. The details of these points are beyond this paper, and since our goal is to present simple equations for objective analysis we use Equation (8) despite its drawbacks.

3. ANALYSIS TECHNIQUES & EXAMPLES

3.1. Spectral Simulator

A spectral simulator program can be used to effectively model performance changes due to changes in the spectral response of the system. We use such a program that considers the spectral reflectance of a target, the spectral distribution of the lighting, the spectral transmission of a lens, the spectral transmission of a set of color filters, and the spectral sensitivity of a light collector (e.g., photocathode). Figure 6(a) shows example spectral responses of a given system with no filter (Black curve) and a set of "leaky" RGB filters with relatively low transmission. Here, the term "leaky" refers to the transmission of NIR in addition to the VIS. Figure 6(b) shows the result of applying these spectral response curves to the spectral reflectances of the Macbeth chart. Figure 6(c) shows an actual image of the Macbeth chart that was taken using a blue-enhanced image-intensified camera with the filters described by Figure 6(a) in nominal "moon-light" conditions (note: this image exhibits noise that is due to low-light conditions under which it was captured). Images 6(b) and (c) have a reddish tint to them, due to the fact that the spectral response of the red filter is greater than the other two filters. These images are "Raw" in the sense that a color transformation matrix has not been applied to properly mix the input filter states into proper RGB display colors.

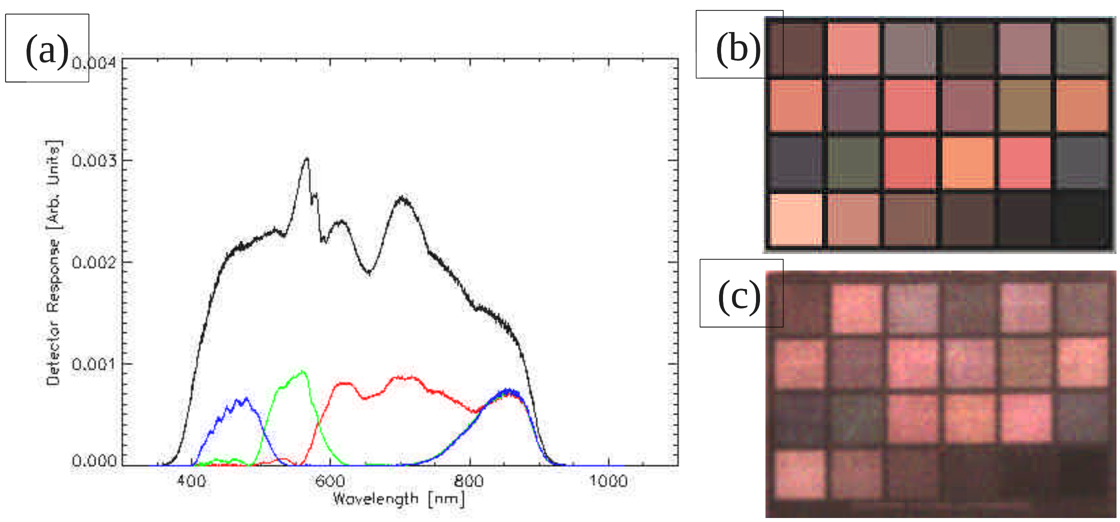
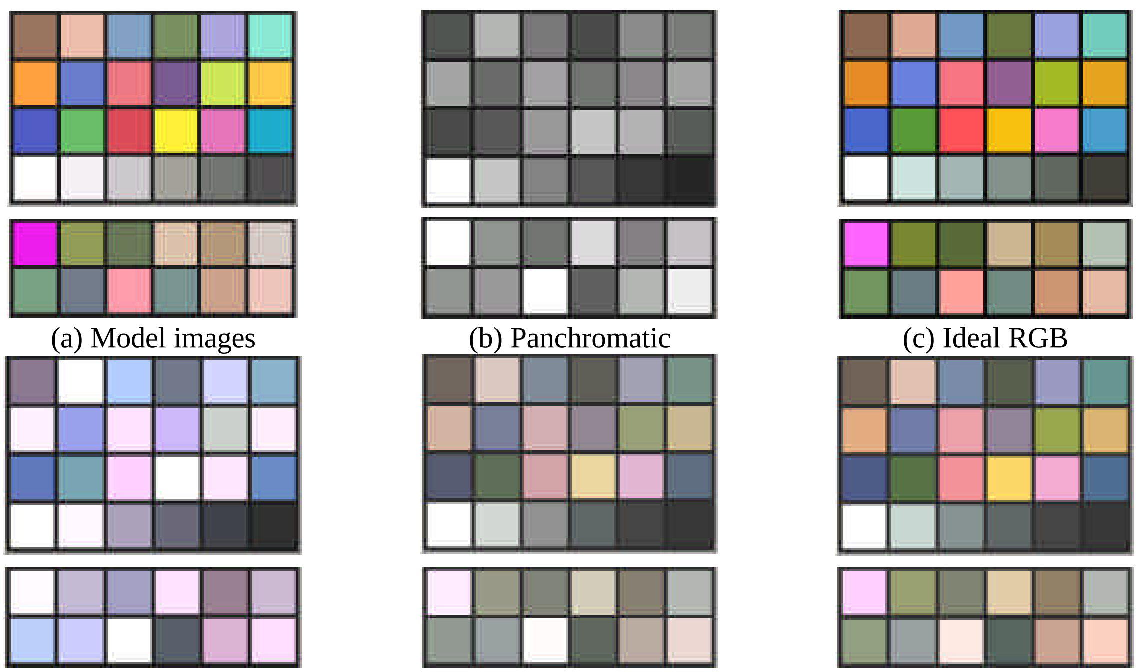


Figure 6. Spectral simulator used for design analysis; (a) Spectral response curves for the system with no filter (black curve) and with RGB filters (colored curves), (b) simulated image of Macbeth chart, and (c) actual image of Macbeth chart taken using blue-enhanced image-intensifier tube and "moonlight" conditions (shown for comparison).

The simple simulator shown here captures the response of the system and can be used in design studies. For more detailed studies, OKSI has also developed a complete Color Night Vision Simulator (output not shown here) that can use a hyperspectral data cube input along with spectral characteristics, and physical characteristics of I2 tube elements and detector, including the system MTF. This program generates full-scene simulations (including noise) under various conditions, noise, etc. By using the FOMs to analyze these simulations, system designs can be further optimized by expanding beyond the available hardware.

3.2. Example analysis

In this section we present an example of applying the FOM analysis to a set of simulated responses. In this example we use several filter states: (1) no filter (panchromatic response), which produces monochrome output; (2) ideal RGB with nearly 100% in-band transmission, but no NIR transmission; (3) leaky RGB, described above with spectral response as shown in Figure 6(a); and (4) OKSI design filter set, with proprietary spectral curves. Color RGB output were simulated using color mixing matrices as described by Equation (2). For the OKSI design we model two different transformation matrices, for the other cases only one matrix, which is optimized for reproduction of the Macbeth chart, was applied. Visual representations of the response for the different cases are shown in Figure 7. For each filter state, the larger chart of 24 squares on the top is the reproduction of the Macbeth chart and the smaller chart of 12 squares on the bottom is the reproduction of the objects in the spectral database shown in Figures 3 and 4. (Of course, the color reproduction of these images for the reader depends upon the monitor or printer used for viewing this paper). Tabulated results of the FOM analysis are shown in Table 2.



(a) Model images (b) Panchromatic (c) Ideal RGB

(d) Leaky RGB (e) OKSI Design T_1 (f) OKSI Design T_2

Figure 7. Simulated images of Macbeth chart (above) and Spectral Database (below) for different filter states.

Table 2. Results of FOM calculations for the simulations shown visually in Figure 7. R_R is calculated relative to the "No Filter" case. Values for the Macbeth chart and Spectral Database are calculated by comparing all possible combinations.

Filter	S_R	N_T	Macbeth Chart			Spectral Database		
			R_R	*ErrC*	Below threshold	R_R	*ErrC*	Below threshold
No Filter (panchromatic)	1.0	1.0	1.00	0.21	13.4%	1.00	0.15	10.6%
Ideal RGB	0.21	1.5	0.89	0.03	0.0%	0.67	0.05	0.0%
Leaky RGB	0.16	1.2	0.60	0.16	1.8%	0.38	0.21	3.0%
OKSI design [T_1]	0.81	1.6	1.16	0.14	0.4%	0.99	0.09	1.5%
OKSI design [T_2]	0.81	3.2	1.44	0.08	0.4%	1.17	0.05	0.0%

The signal value S is calculated for a perfect reflector, the noise parameter N_T is calculated based on each transformation matrix, and R_R is calculated relative to the "No Filter" case. To calculate values for the Macbeth chart and the Spectra Database, we compared all possible combinations in each case. For instance, the Relative Range equation depends upon the contrast. To find one value for the Macbeth chart, the median value for the contrast of all possible combination of squares is used. Likewise the "Below Threshold" value is the percentage of pairs that have a contrast less than 0.05.

The FOMs quantitatively describe the differences between the relative performances of similar systems with the different filter states. For example, from the images in Figure 7 it is easy to see that the color reproduction with the Leaky RGB filter is poor. This is reflected by relatively large values of *ErrC*. The reason for this poor color reproduction is due to improper inclusion of the NIR signal. In comparison the two OKSI designs, which do a better job of including NIR radiation, have much better color reproduction and lower values of *ErrC*, particularly for the spectral database. In comparing the two OKSI designs to each other, one can see that the [T_2] has better color reproduction. The price for this better color reproduction is in turn quantified by a larger transformation noise N_T. The "below threshold" metric describes a primary advantage of color vs. panchromatic, in that color (even in the case of the Leaky RGB) gives the ability to distinguish more combinations of targets. The Relative Range equation is the most difficult to verify with a simulation such as this; however, it is still useful in providing a way to compare different designs. For example, in comparing the Ideal RGB filters to the OKSI custom filters, one can see that even though the color reproduction and contrast is better with the Ideal RGB, the OKSI design has a much longer range due to a much larger signal.

In the example shown above, we only simulate one lighting condition and one light collector. One could easily recalculate the FOMs for simulations of other lighting conditions, different photocathode response curves, etc. In addition, we reiterate that for a means of objectively testing and comparing real sensors, all of these metrics can be applied to actual images taken with different cameras or to full-scene simulations of various objects and backgrounds of interest.

4. CONCLUSIONS

Figures of Merit (FOMs) are described that allow for the simple objective quantification of True-Color Image-Intensified (TC-I2) cameras. The FOMs are particularly useful in designing systems, since they allow for extensive engineering tradeoff studies without the need for actual engineering design, development, and fabrication of various components, and without the need for time consuming human trials. The benefits of different designs depend on the color transformation, the lighting, and the objects of interest; and these techniques allow for the quantitative assessment of the performance of TC-I2 systems while varying all these conditions. OKSI has used these FOMs to help in the design of TC-I2 camera systems and is now also using the FOMs to optimize and characterize these color low-light-level systems. The FOMs can also be use to objectively compare the performance of existing fused I2/TIR false-color images to I2 monochrome images and for the design of better fusion techniques.

5. ACKNOWLEDGEMENTS

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