The Influence of Sensor Spectral Sensitivities on Illuminant Estimation Methods

Xiaoyun Jiang and Mark D. Fairchild
Munsell Color Science Laboratory, Rochester Institute of Technology
Rochester, New York

Abstract

The spectral characteristics of sensor sensitivities are an important component of image signal formation and also essential knowledge for illuminant estimation methods. Due to the wide variation of sensor spectral sensitivities in cameras, the efficiency of illuminant estimation methods could also be affected. In this paper, we study the influence of sensor variation on the efficiency of different illuminant estimation methods, and find out the type of sensor sensitivities that have better performance for corresponding methods. Also, we propose a way of using spectral sensitivity replacement for methods to be applicable with unknown sensor information. The optimal replacing sensor sensitivities can be obtained through testing on a series of sensor combinations. In addition, the testing result reveals the efficiency descent degrees for those methods when using the replacing sensors. Those insensitive to incorrect sensor information are better methods to be applied to images with unknown spectral sensitivities.

Introduction

The formation of image signals depends on three factors, surface spectral reflectances, illumination, and camera sensor sensitivities. In color constancy research, one main purpose is to extract the characteristics of illuminations or surface reflectances from camera output signals with the information of sensor sensitivities that the images were taken with. Although sensor spectral sensitivities are normally treated as given information in most illuminant estimation methods, due to their wide variation in real image capture systems, it would be helpful to see the affects of sensor variation on the efficiency of different methods.

There have been some former studies about the influence of sensor sensitivities on color constancy algorithms. It has long been noticed that von Kries adaptation model has its limitations in real color transformation.[1,2] Only when receptor spectral sensitivities are narrow and do not overlap, the von Kries model could be ideal. Based on this, Finlayson *et al*. proposed the idea of sensor spectral sharpening, which uses a linear transformation to convert original sensor sensitivities into a new set of sensitivities to optimize the diagonal model.[3,4] Barnard tested the sensor sharpening method, and found out that the efficiency is highly dependent on both the sensors and the algorithms. Besides, the introduction of negative values could yield poor results.[5,6] When evaluating linear models of surface spectral reflectance, Maloney discussed the role of photoreceptors in spectral recovery from color signals and made the conjecture that the broad, smooth shape of the spectral sensitivities enhances the constraints on surface reflectance functions.[7] Cardei *et al*. studied the problem of white-point estimation for uncalibrated images.[8] For the problem of non-linearity characteristics in cameras, they concluded that the diagonal model used for linear images also works in the case of gamma corrected images. The problem of unknown white-balance could be absorbed into the diagonal transformation which is required for color correction.

In spite of all the above studies, it still would be helpful to have a systematic study about the influence from sensor variation on different kinds of illuminant estimation methods. As we know, image capturing systems have quite different selections of sensor spectral sensitivities. Also there is wide variation in illuminant estimation methods. Since the role of sensor sensitivities is different in the performance of different methods, they will cause different degrees of affects. In this paper a series of experiments is presented to see such influence. Basically, three types of methods are tested here, those based on simple diagonal transformations, those based on gamut comparisons, and those based on spectral recoveries.

Another problem studied in this paper is, how could methods be applicable with unknown sensor information? In many cases, images are given without the information of camera spectral sensitivities. Illuminant estimation for such images would be harder since it adds even more unknowns to the original under-constrained problem. For most illuminant estimation methods, knowledge of sensor spectral characteristics is necessary in their application. Cardei studied this problem and proposed the efficiency comparisons on methods such as gray world, maximum RGB and neural network for images with unknown spectral senstivities.[8] But these methods just represent the small subset for which the sensor information is not necessary. For other methods that require sensor sensitivities in their performance, here we study the possibility for them to be applicable when such information is not available.

When the original spectral sensitivities are unknown, one possible way is to find alternative information to take their place. In this paper, we use some assumed spectral sensitivity to make replacement. Through testing a series of sensor combinations, the optimal replacing sensor sensitivities can be obtained. The testing also suggests the feasibility for the method to be applicable to images with unknown spectral sensitivities.

Simulation of Spectral Sensor Sensitivities

In real cameras, the selection of the three channel sensor sensitivities could be very different. In order to study the wide variation of sensor selections, we use cubic spline functions to simulate the real sensitivity functions. Although in general real spectral sensitivities are more complicated than the cubic spline functions, these curves have proven to be very effective in sensor sensitivity simulations,[9,10] and their characteristics are easier to analyze. The simulated curves contain the main properties of real sensitivities, such as the peak wavelength and the width. The variation of the overlaps between different channels can also be simulated through different combinations of the three channels.

In this paper, the problem of different white-balance is not considered with the assumption that such problem could be absorbed in diagonal transformation.[8] So all the simulated sensor sensitivities are white-balanced to the same illumination. From the properties of many real camera sensitivities, and also from the study on optimal camera spectral sensitivities,[10, 11] the peak-wavelengths and the half-widths are selected as in Table 1 for creating the simulated sensor sensitivities with cubic spline functions.

Table 1. Selections of the Peak-Wavelength and the Half-Width Parameters for Simulated Sensor Sensitivities

	Peak-wavelength (nm)		Half-width (nm)	
Red	580	620	40	60
Green	530	550	45	65
Blue	450	470	35	55

In order to control the total number of tested sensor combinations, for each channel only two peak-wavelengths and two half-widths are selected. So there are 4 different selections for each channel, and altogether 64 sensor combinations are simulated. Those sensor sensitivities contain different characteristics in each channel, and their combinations simulate different degrees of overlaps between the three channels. Figure 1 shows some of the simulated sensitivities, with the example of different combinations on red and green channels. Through a series of experiments on the simulated 64 sensor combinations, the influences of sensor variation on output color signals, color gamut ranges, and on the efficiency of different illuminant estimation methods are investigated.

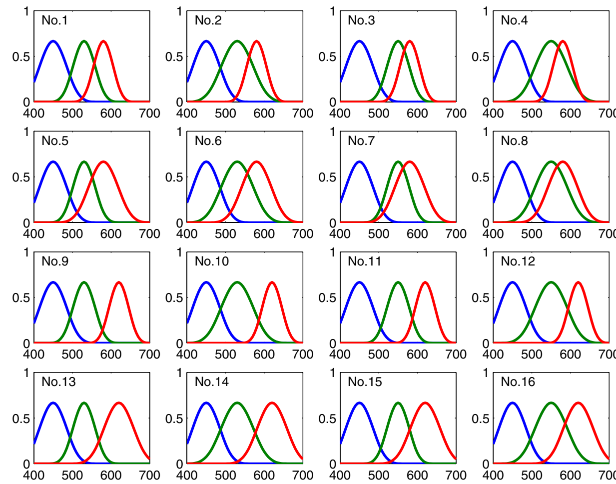


Figure 1. Part of simulated sensor sensitivities with different combinations in red and green channel.

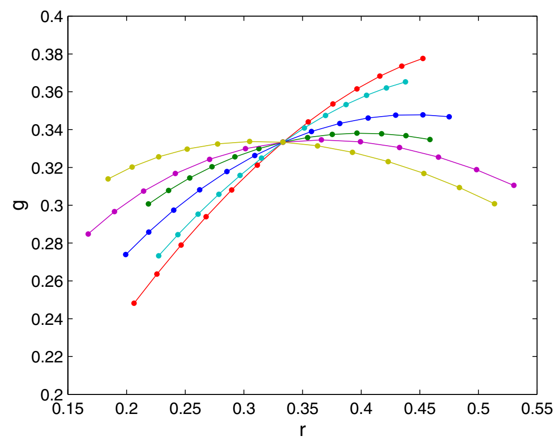
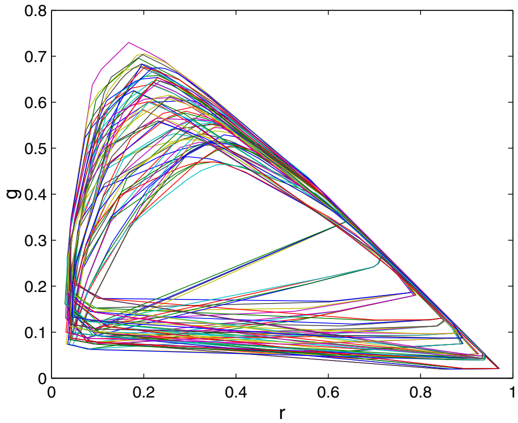
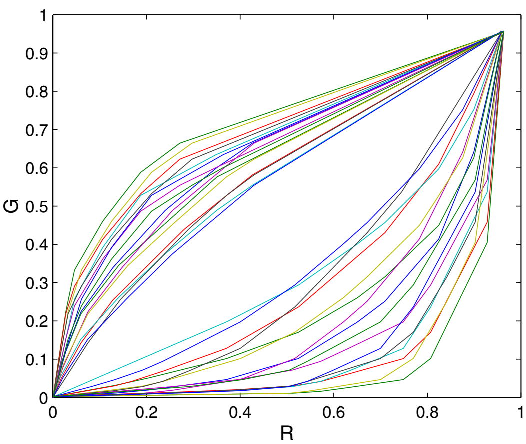


Figure 2. Examples of chromaticity variation in (r, g) space for different illuminations caused by sensor variation.

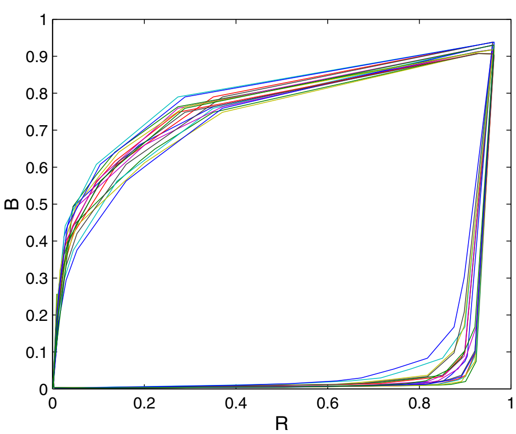
It has been widely known that different cameras will output different image signals for the same scene, even though they have been white-balanced to the same illumination. Besides, the variation of sensors will also create large variation in the chromaticities of illuminations, as in Figure 2. It shows the chromaticities in (r, g) space of the blackbody radiations with CCT 2500 to 8000K through different kinds of sensor combinations. They clearly follow different tracks. In addition, the variation in color signals caused by sensor variation will also create variation in color gamuts. Figure 3 (a), (b) and (c) show such gamut variation in the color space as (r, g), (R, G) and (R, B). Although all those gamuts are created with the same spectral reflectance database and under the same illumination that all the sensor combinations are white-balanced with, sensor variation still have large affects on the gamut shapes and areas, especially for those in (r, g) and (R, G) spaces.



(a)



(b)



(c)

Figure 3. Examples of gamut variation in different color spaces caused by sensor variation. (a) In (r, g) space; (b) in (R, G) space; (c) in (R, B) space.

Influences of Sensor Sensitivities on Illuminant Estimation Methods

There is wide variation in illuminant estimation methods. Typically, their basic principles could be divided into two groups. One is through statistical estimation, and the other is through some physical properties such as highlights and mutual reflectances.[12-15] For the former group, there are three types of algorithms. The first type is through some simple diagonal transformations of the color signals, for example the gray world and the maximum RGB methods; the second type is through different kinds of gamut comparisons between the image gamuts and the reference gamuts, such as 3-D gamut mapping,[16] color by correlation,[17] sensor correlation[18,19], and so on; and the third type is through spectrally recovering the illuminant power distributions and the surface reflectances with a linear model, such as Maloney-Wandell method[20] and illuminant detection in linear space.[21] In this paper, we examine the influence of sensor sensitivities on the three types of methods. Since the wide variation of sensor sensitivities are realized through simulation, the images used in this paper for testing different method efficiency are also synthetic images. Those images are created with surface reflectance randomly selected from a wide range spectral reflectance database, and the illuminations randomly selected from blackbody radiations with CCT ranging from 2500K to 8000K. For each sensor combination studied in this paper 1000 synthetic images are created. All the 64,000 images are tested for different kinds of methods. Through comparing the method efficiency between different sensor combinations, the influence of sensor sensitivities on this method is determined.

The Influence on the Methods Based on Color Signal Transformations

Some illuminant estimation methods are based on direct diagonal transformations on sensor output signals to adjust the images and to obtain the chromaticities of the illuminations. Although the spectral information of sensor sensitivities is not necessary in their implementations, since color signals are affected by spectral sensitivities, the variation of sensors still have some influence on the efficiency of those methods. Two methods, gray world and maximum RGB, are tested in this experiment to see the influence of sensor variation. For each studied sensor combinations, 1000 synthetic images are tested and the results are analyzed. The estimation errors from the two methods are normally measured as the Euclidean distances between the real illuminants and the estimated illuminants in (r, g) space. Since, as shown in Figure 2, chromaticities of illuminations are quite different because of sensor variation, the Euclidean distances representing the estimation errors are normalized with the average distances between each illumination chromaticities to the standard white.

The mean estimation error for each sensor combination is treated as the criterion of method efficiency. Their statistical analysis from gray world and maximum RGB methods is shown in Table 2, which includes the maximum, minimum, mean and standard deviation of the mean estimation errors obtained from the tested 64 sensor combinations. And "std_norm" represents the normalized standard deviation, which is the ratio between the standard deviation and mean value. This value can be used to compare the efficiency variation caused by sensor differences between different methods. Data in Table 2 show that maximum RGB has better average efficiency than gray world. The variation of sensor combination cause medium affects on both the two methods.

Table 2. Data analysis of Mean Estimation Errors as Euclidean Distance in (*r*, *g*) Space for Gray World and Maximum RGB Methods.

	min	max	mean	std	std_norm
GW	0.042	0.059	0.052	0.0052	0.10
MRGB	0.019	0.029	0.024	0.0020	0.084

From data analysis, gray world method has peak-wavelength in red channel as the main factor affecting method efficiency. The sensor combinations with small estimation errors have red and green channels with larger overlaps. For maximum RGB method, the sensor combinations with better performance are those at the right corner in Figure 1, that is, No. 7, 8, 3 and 4, which also have large overlaps in red and green channels. So, for these two methods, sensor sharpening is not necessary to obtain better estimation efficiency.

The Influence on Gamut Comparison Methods

Generally in gamut comparison methods, illuminants are estimated through comparing the image gamuts and the reference gamuts. Spectral characteristics of sensor sensitivities are necessary in establishing the reference gamuts. From previous discussion of Figure 3, the variation in sensor sensitivities could cause large variation in color gamuts. For example in (*r*, *g*) space, sensor combinations with large overlaps in red and green channels have small gamut areas, and those with small overlaps have large gamut areas. Such large variation in gamut will also cause the variation in method efficiency due to different sensor sensitivities.

Two gamut mapping methods are tested in this experiment to see the influence from sensor sensitivities. One is color by correlation, which is performed in (*r*, g) space, and the other is sensor correlation method, which is performed in a normalized (*R*, *B*) space. For the former one, all the 64 sensor combinations are tested, and for the later one, only 16 sensor combinations are tested since green channel has no affects on the (*R*, *B*) space.

For the above two methods, Table 3 describes the data analysis of the mean estimation errors from different sensor combinations. The normalized standard deviation shows that the efficiency of color by correlation method is strongly affected by the selection of sensor combination, since the value from this method is almost 7 times that from sensor correlation method. From the testing results, the main factor in sensors that influences the efficiency of color by correlation is their overlap degree. Those having small overlaps between each channel will have better performance, for example sensor combinations such as No. 11 and 15 in Figure 1 have the lowest estimation errors. As a result, sensor sharpening should be helpful in improving the efficiency of this method. The variation in sensor sensitivities has much less influence on the sensor correlation method comparatively. The main factor in sensor combination is the peak-wavelength of red and blue channels. The sensor sensitivities with small overlaps do not necessarily have better efficiency.

As previously introduced, another task in this paper is to study the problem for the methods to be performable even without the spectral characteristics of the original sensitivities. In gamut comparison methods, the unknown information can be replaced by some assumed spectral sensitivities in establishing reference gamuts. In order to find out the suitable replacing one in each method, a series of sensor combinations are tested on large numbers of images that were created with different kinds of sensor sensitivities. The sensor sensitivities with lower estimation errors are better selections to be the replacement for this method. In this experiment, large numbers of synthetic images are created with different kinds of sensor sensitivities, and the 64 sensor combinations as studied previously are tested to find out the optimal one. When methods are performed with the assumed sensor sensitivities, method efficiency would be decreased because of the gamut difference caused by incorrect sensor information. The efficiency descent degree demonstrates whether the method is suitable to be performed with unknown sensor sensitivities or not. Methods with low descent degrees would be better selections for illuminant estimation in such cases.

Table 3. Data Analysis of Mean Estimation Errors as the Difference in Mired for Color by Correlation and Sensor Correlation Methods.

	min	max	mean	std	std_norm
CbyC	0.47	6.94	2.70	1.42	0.53
SC	13.40	17.48	15.63	1.24	0.079

Table 4. Data Analysis of Mean Estimation Errors as the Difference in Mired for Color by Correlation and Sensor Correlation Methods with Unknown Sensors.

	min	max	mean	std	std_norm
CbyC	35.38	51.17	41.62	4.03	0.10
SC	16.57	23.01	19.10	2.29	0.12

Both color by correlation and sensor correlation methods are tested for images with unknown sensor sensitivities. The statistical information for those mean estimation errors is in Table 4. For color by correlation method with incorrect sensor sensitivities, the mean estimation error is almost 15 times those with original sensitivities. But for sensor correlation method, the mean estimation errors are only 22% higher when using the replaced sensitivities. Although originally the estimation efficiency from color by correlation is better than that from sensor correlation method, when using the replaced sensor sensitivities, the efficiency from the former method is much worse than the latter one. From the above data analysis, sensor correlation method is less sensitive to incorrect spectral sensitivities, and is the better method selection in illuminant estimation when applying to images with unknown sensors. The main reason for the later method to have better performance is because color signals have been normalized in the method and the reference gamuts in (R, B) space will have smaller variation for different kinds of sensor combinations. While color by correlation method is tested to be unsuitable for images with unknown sensor sensitivities, for sensor correlation method, the optimal replacing sensor combinations are the same as those having best performance with original sensor information.

The Influence on Spectral Recovery Methods

Some illuminant estimation methods, such as Maloney-Wandell method and illumination detection in linear model, spectrally recover the illuminant power distribution and the surface reflectance from sensor output signals. Since the sensor spectral sensitivities are essential in forming color signals, they are also necessary in recovering illuminations from color signals. The influence of sensor sensitivities on this kind of method is mainly during the spectral recovery processing, which extracts the combined spectral information of illumination power distributions and surface reflectances from color signals. There are several methods used in spectral recovery, and the most widely used is the linear model, which expresses spectral information as linear combinations of some eigenvectors, for example those from PCA analysis. Besides, Maloney proposed some weighted linear recovery method with considering the affect of the receptor sensitivities.[7] Recently, the Wiener analysis method has become popular in getting better spectral recovery efficiency.[22]

In this experiment, the influence of sensor variation on spectral recovery efficiency is tested through two spectral recovery methods, PCA analysis and Wiener analysis. Generally the spectral recovery efficiency is judged as the correlation coefficient R^2 between the original and the recovered spectral curves. The average R^2 from large numbers of spectral recoveries can be treated as the criterion of the method efficiency. For each of the studied 64 sensor combinations, about 2000 spectral reflectances are recovered from the simulated color signals. The mean R^2 values are calculated for each sensor combinations and their statistical properties are shown in Table 5. The spectral recovery efficiency from Wiener analysis is a little better than that from PCA method. Through the normalized standard deviation, the variation in spectral recovery efficiency caused by sensor difference are small for both PCA and Wiener method comparing to the other methods discussed previously. So the selection of sensor sensitivities does not obviously affect the method efficiency.

Table 5. Data Analysis of Spectral Recovery Efficiency as R^2 for PCA and Wiener Methods

	min	max	mean	std	std_norm
PCA	0.64	0.73	0.70	0.028	0.039
Wiener	0.71	0.75	0.73	0.013	0.018

The above two spectral recovery methods are also tested with unknown sensor sensitivities. In this experiment, large numbers of color signals are created with different kinds of sensor sensitivities, and all the 64 sensor combinations are tested as the assumed spectral sensitivities to see the spectral recover efficiency of these two methods with incorrect sensors. The statistical properties of the tested mean R^2 values are shown in Table 6. The recovery efficiencies for both methods are a little decreased from those with original sensor information. But the descent degrees are small comparing to gamut comparison methods, only about 7% for PCA analysis and about to 5% for Wiener analysis. It is a little surprising that in spite of the huge variation in color signals caused by the sensor variation, the spectral recovery results are not very sensitive to incorrect sensor information. The reason may be that originally the spectral recovery from only three sensor output signals are not very accurate, and the decrease caused by incorrect sensitivities does not appear very significant. So illuminant estimation methods based on spectral recovery could be applied to images without sensor information. Only the method efficiency is a little decreased when using the replacing spectral sensitivities. Besides, since the normalized standard deviations in Table 6 are also small for both methods, there is not much difference in the selection of sensor sensitivities to be the replacement when applying to images with unknown sensors.

Table 6. Data analysis of Spectral Recovery Efficiency as R^2 for PCA and Wiener Methods with Unknown Sensors

	min	max	mean	std	std_norm
PCA	0.57	0.68	0.65	0.026	0.040
Wiener	0.65	0.71	0.69	0.014	0.020

Conclusions

In this paper we studied the influence of sensor sensitivities on the efficiency of illuminant estimation methods. First, the influence is highly dependent on methods. The normalized standard deviation of the testing results could reveal the degree of influence from sensor sensitivities. For gray world and Maximum RGB methods, they have medium influence on method efficiency. For gamut comparison method, the variation in reference gamuts caused by sensor differences highly affects the method efficiency. For different methods, the influence degrees are also very different. For example color by correlation has method efficiency very sensitive to sensor difference, but their influence on sensor correlation method is medium. Sensor variation has small influence on spectral recovery methods when recovering from trichromatic values. Second, the types of sensor sensitivities to have better performance in different methods are also different. For example for color by correlation method, small overlaps between each channel will obtain better efficiency, but it is not necessary for the other methods. In addition, although spectral sensitivities are necessary in many illuminant estimation methods, we proposed a possible way of using replacement to make them applicable even without sensor information. We also studied the method efficiency descent degree with incorrect sensor sensitivities. Those with less decreasing in method efficiency are more suitable to be applied to images with unknown sensor sensitivities. In gamut comparison methods, it was found that color by correlation is much more sensitive to incorrect sensor information than sensor correlation method. So the later method is a better selection with unknown sensor information. For the methods based on spectral recovery from three sensor outputs, both PCA and Wiener analysis can be applied to images with unknown sensors.

References

1. J. A. Worthey, Limitations of color constancy, *J. Opt. Soc. Am. A*, vol. **2**, no. 7, pp. 1014-1026 (1985).
2. J. A. Worthey and M. H. Brill, Heuristic analysis of von Kries color constancy, *J. Opt. Soc. Am. A*, vol. **3**, no. 10, pp. 1708-1712 (1986).
3. G. D. Finlayson, M. S. Drew, and B. V. Funt, Spectral sharpening: Sensor transformations for improved color constancy, *J. Opt. Soc. Am. A*, vol. **11**, no. 5, pp. 1553-1563 (1994).
4. M. S. Drew and G. D. Finlayson, Device-independent color via spectral sharpening, *Proc. IS&T/SID Second Color Imaging Conference*, pp. 121-126, 1994.
5. K. Barnard and B. Funt, Experiments in sensor sharpening for color constancy, *Proc. IS&T/SID Sixth Color Imaging Conference*, pp. 43-46, 1998.
6. K. Barnard, F. Ciurea and B. Funt, Sensor sharpening for computational colour constancy, *J. Opt. Soc. Am. A*, vol. **18**, No. 11, pp. 2728-2743 (2001).
7. L. T. Maloney, Evaluation of linear models of surface spectral reflectance with small numbers of parameters, *J. Opt. Soc. Am. A*, vol. **3**, no. 10, pp. 1673-1683 (1986).
8. V. C. Cardei, B. V. Funt and K. Barnard, White point estimation for uncalibrated images, *Proc. IS&T/SID Seventh Color Imaging Conference*, pp. 97-100, 1999.
9. N. Ohta, Optimization of spectral sensitivities, *Photographic Science and Engineering*, vol. **27**, no. 5, pp. 193-201 (1983).
10. S. Quan, N. Ohta, and N. Katoh, Optimization of camera spectral sensitivities, *Proc. IS&T/SID Seventh Color Imaging Conference*, pp. 273-278, 2000.
11. S. Quan and N. Ohta, Evaluating hypothetical spectral sensitivities with quality factors, *J. Imaging Sci. and Tech.*, vol. **46**, no. 1, pp. 8-14 (2002).
12. H. C. Lee, Method for computing the scene-illuminant chromaticity from specular highlights, *J. Opt. Soc. Am. A*, vol. **3**, no. 10, pp. 1694-1699 (1986).
13. S. Tominaga, Surface identification using the dichromatic reflection models, *Trans. Pattern Analysis and Machine Intelligence*, vol. **13**, no. 7, pp. 658-670 (1991).
14. B. V. Funt, M. S. Drew, and J. Ho, Color constancy from mutual reflection, *Int. J. Computer Vision*, vol. **6**, pp. 5-24 (1991).
15. B. V. Funt and M. S. Drew, Color space analysis of mutual illumination, *Trans. Pattern Analysis and Machine Intelligence*, vol. **15**, pp. 1319-1326 (1993).
16. D. A. Forsyth, A novel algorithm for color constancy, *Int. J. Computer Vision*, vol. **5**, pp. 5-36 (1990).
17. G. D. Finlayson, P. Hubel, and S. Hordley, Color by correlation, *Proc. IS&T/SID Fifth Color Imaging Conference*, pp. 6-11, 1997.
18. S. Tominaga, S. Ebisui, and B. A. Wandell, Color temperature estimation of scene illumination, *Proc. IS&T/SID Seventh Color Imaging Conference*, pp. 42-47, 1999.
19. S. Tominaga, A. Ishida, and B. A. Wandell, Further research on the sensor correlation method for scene illuminant classification, *Proc. IS&T/SID Eighth Color Imaging Conference*, pp. 189-194, 2000.
20. L. T. Maloney and B. A. Wandell, Color constancy: a method for recovering surface spectral reflectance, *J. Opt. Soc. Am. A*, vol. **3**, pp. 29-33 (1986).
21. B. Tao, I. Tastl, and N. Katoh, Illumination detection in linear space, *Proc. IS&T/SID Eighth Color Imaging Conference*, 172-177 (2000).
22. W. K. Pratt and C. E. Mancill, Spectral estimation techniques for the spectral calibration of a color image scanner, *Applied Optics*, vol. **15**, pp. 73-75 (1976).

Biography

Xiaoyun Jiang received her BS in 1993 and MS in 1996, both from the Department of Optical Engineering, Beijing Institute of Technology. From 1996 to 1998, She was an Assistant Engineer in the Institute of Mechanics at the Chinese Academy of Science where she worked on opto-electronics and instrumental optics. Now she is a Ph.D. candidate in the Imaging Science Program in the Center for Imaging Science with Rochester Institute of Technology. Her work primarily focuses on illuminant estimation and color constancy research.