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Colorimetric Characterization of a Desktop Drum Scanner

Using a Spectral Model

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A thesis submitted for partial fulfillment
of the requirements for the degree of
Master of Science in Color Science
in the Center for Imaging Science
in the College of Imaging Arts and Sciences
of the Rochester Institute of Technology

July 1994

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M. S. DEGREE THESIS

The M. S. Degree Thesis of Ming-Ching James Shyu
has been examined and approved
by two members of the color science faculty
as satisfactory for the thesis requirement for the
Master of Science degree.

Dr. Roy Berns, Thesis Advisor

Dr. Mark Fairchild

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ABSTRACT

A scanner characterization method based on an analytic spectral model was derived. The method first modeled the spectral formation of each medium using either Beer-Bouguer Law or Kubelka-Munk theory. Scanner digital counts were then empirically related to dye concentrations. From these estimated dye concentrations, either spectral transmittance or spectral reflectance factor could be predicted. These estimated spectral data were used to calculate tristimulus values and then color differences for the target object. A Howtek D4000 desktop drum scanner was colorimetrically characterized accordingly. The average characterization errors were all less than CIELAB color difference of 1.0 for Kodak IT8.7/1, Kodak Q-60C, Fuji IT8.7/1, and Fuji IT8.7/2 targets via this method.

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Dedicate to
Yu-Ling,
Julia and my parents

Table of Contents

Table of Contents.....	i
List of Tables	iv
List of Figures	vi
1. Introduction.....	1
2. Background.....	4
3. Scanner Characterization Process	13
3.1 Material Analysis	14
3.1.1 Spectral Model - Transparent Material.....	15
3.1.2 Spectral Model - Opaque Material.....	18
3.1.3 Derivation of Unit Absorptivities.....	20
3.2 Prediction of Actual Concentrations.....	22
3.3 Building Characterization Model.....	25
3.3.1 Linearizing Scanner Signals	27
3.3.2 Relating Scanner Readings to Concentration	28
3.4 Model Verification.....	29
3.5 Comparison with prior spectral methods	32
4. Experimental.....	33
4.1 Target Objects.....	33
4.2 Metrology and Colorimetry.....	34
4.3 Spectral Measurement.....	37
4.3.1 Transparent Target	37
4.3.2 Reflection Target	38

4.4 System Configuration.....	38
5. Results and Discussion.....	40
5.1 Transparent Material - Kodak Ektachrome	40
5.1.1 Material Analysis.....	40
5.1.2 Prediction of Actual Concentrations	45
5.1.3 Image Scanning	46
5.1.4 Building Characterization Model	47
5.1.5 Performance Verification.....	69
5.2 Transparent Material - Fuji Fujichrome	72
5.2.1 Material Analysis.....	72
5.2.2 Prediction of Actual Concentrations	77
5.2.3 Image Scanning	78
5.2.4 Building Characterization Model	78
5.2.5 Performance Verification.....	86
5.3 Opaque Material Kodak Ektacolor Plus Paper.....	89
5.3.1 Material Analysis.....	89
5.3.2 Prediction of Actual Concentrations	94
5.3.3 Image Scanning	95
5.3.4 Building Characterization Model	96
5.3.5 Performance Verification.....	105
5.4 Opaque Material - Fuji Fujicolor Paper	108
5.4.1 Material Analysis.....	108
5.4.2 Prediction of Actual Concentrations	113
5.4.3 Image Scanning	114

5.4.4 Building Characterization Model	114
5.4.5 Performance Verification.....	124
6. Conclusions.....	131
References.....	134
Appendix A: Spectral Weightings for Calculating Tristimulus Values.....	139
Appendix B: Spectral Property of the Target Materials	141
Appendix C: Program to Predict Concentrations	145
Appendix D: Program to Calculate Color Difference.....	155
Appendix E: Program to retrieve Raw Scanner Digital Counts	163
Appendix F: A Problem in the 12-bit Scanner Signal.....	172

List of Tables

TABLE I. List of published scanner characterization results.....	12
TABLE II. Results of the principal component analysis on Kodak IT8.7/1 target	42
TABLE III. Regression results - ramp eigenvectors against global eigenvectors for Kodak IT8.7/1 target.....	43
TABLE IV. Regression results of the 3 by 3 model (12-bit scan) for Kodak IT8.7/1 target	50
TABLE V. Regression results of the 3 by 11 model (12-bit scan) for Kodak IT8.7/1 target	55
TABLE VI. Regression results of the 3 by 11 model (8-bit scan) for Kodak IT8.7/1 target	61
TABLE VII. Performance summary of 3 different scanner models for Kodak IT8.7/1 target.	66
TABLE VIII. Results of the principal component analysis on Fuji IT8.7/1 target	74
TABLE IX. Regression results - eigenvectors against global eigenvectors for Fuji IT8.7/1 target	75
TABLE X. Regression results of the 3 by 11 model (12-bit scan) for Fuji IT8.7/1 target	81
TABLE XI. Results of the principal component analysis on Kodak Q-60C target.....	91
TABLE XII. Regression results - ramp eigenvectors against global eigenvectors for Kodak Q-60C target.....	92
TABLE XIII. Regression results of the 3 by 11 model (8-bit scan) for Kodak Q- 60C target	99

TABLE XIV. Results of the principal component analysis on Fuji IT8.7/2 target	110
TABLE XV. Regression results - ramp eigenvectors against global eigenvectors for Fuji IT8.7/2 target.....	111
TABLE XVI. Regression results of the 3 by 11 model (8-bit scan) for Fuji IT8.7/2 target	118
TABLE XVII. Regression results - the independent Fujicolor target's eigenvectors against the Fuji IT8.7/2 target's eigenvectors.....	130
TABLE XVIII. Summary of the scanner characterization results.	131

List of Figures

FIG. 3-1. Overall data flow of the characterization method.....	14
FIG. 3.1-1. Optical geometry of transmittance and opaque materials.....	15
FIG. 3.3-1. Plots of normalized scanner readings against concentration readings for spectrally non-selective colors	27
FIG. 3.4-1. Flow chart of the characterization process.....	31
FIG. 4.1-1. Sample images of the target materials	36
FIG. 5.1-1. Maximum transmittance of Kodak IT8.7/1 target.	41
FIG. 5.1-2. Eigenvectors of Kodak IT8.7/1 target.	45
FIG. 5.1-3. Predicted spectral transmittance factors from the tristimulus matching algorithm.	46
FIG. 5.1-4. Histogram of the ΔE^*_{ab} from the tristimulus matching algorithm for Kodak IT8.7/1 target.....	46
FIG. 5.1-5. Example plots of the linearization process for Kodak IT8.7/1 target.....	49
FIG. 5.1-6. Concentration differences from the 3 by 3 model prediction (12-bit scan) against actual concentrations for Kodak IT8.7/1 target.....	51
FIG. 5.1-7. Histogram of the ΔE^*_{ab} error from the 3 by 3 model (12-bit scan) for Kodak IT8.7/1 target.....	52
FIG. 5.1-8. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 3 model (12- bit scan) for Kodak IT8.7/1 target.....	53
FIG. 5.1-9. Concentration differences from the 3 by 11 model prediction (12-bit scan) against actual concentrations for Kodak IT8.7/1 target.....	56

FIG. 5.1-10. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (12-bit scan) for Kodak IT8.7/1 target	57
FIG. 5.1-11. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (12-bit scan) for Kodak IT8.7/1 target.....	58
FIG. 5.1-12. Concentration differences from the 3 by 11 model prediction (8-bit scan) against actual concentrations for Kodak IT8.7/1 target	62
FIG. 5.1-13. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (8- bit scan) for Kodak IT8.7/1 target.....	63
FIG. 5.1-14. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (8-bit scan) for Kodak IT8.7/1 target.....	64
FIG. 5.1-15. Model performance analysis for the gray balance of Kodak IT8.7/1 target	67
FIG. 5.1-16. Model performance analysis for the hue shift of Kodak IT8.7/1 target	69
FIG. 5.1-17. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (12-bit scan) for an independent Kodak Ektachrome target	70
FIG. 5.1-18. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (12-bit scan) for an independent Kodak Ektachrome target.....	71
FIG. 5.2-1. Maximum transmittance of Fuji IT8.7/1 target.....	73
FIG. 5.2-2. Eigenvectors of Fuji IT8.7/1 target.....	76
FIG. 5.2-3. Histogram of the ΔE^*_{ab} from the tristimulus matching algorithm for Fuji IT8.7/1 target.....	77
FIG. 5.2-4. Example plots of the linearization process for Fuji IT8.7/1 target.....	80
FIG. 5.2-5. Concentration differences from the 3 by 11 model prediction (12-bit scan) against actual concentrations for Fuji IT8.7/1 target.	82

FIG. 5.2-6. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (12-bit scan) for Fuji IT8.7/1 target.....	83
FIG. 5.2-7. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (12-bit scan) for Fuji IT8.7/1 target.....	84
FIG. 5.2-8. Model performance analysis for the gray balance of Fuji IT8.7/1 target.....	85
FIG. 5.2-9. Model performance analysis for the hue shift of Fuji IT8.7/1 target.....	86
FIG. 5.2-10. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (12-bit scan) for an independent Fujichrome target.....	87
FIG. 5.2-11. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (12-bit scan) for independent Fujichrome target.....	88
FIG. 5.3-1. Maximum reflectance of Kodak Q-60C target.	90
FIG. 5.3-2. Eigenvectors of Kodak Q-60C target.	93
FIG. 5.3-3. Measured and predicted spectral reflectances from the tristimulus matching algorithm for Q-60C target.....	95
FIG. 5.3-4. Histogram of the ΔE^*_{ab} from the tristimulus matching algorithm for Kodak Q-60C target.....	95
FIG. 5.3-5. Example plots of the linearization process for Kodak Q-60C target.....	99
FIG. 5.3-6. Concentration differences from the 3 by 11 model prediction (8-bit scan) against actual concentrations for Kodak Q-60C target.	102
FIG. 5.3-7. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (8-bit scan) for Kodak Q-60C target.....	103
FIG. 5.3-8. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (8-bit scan) for Kodak Q-60C target.....	104

FIG. 5.3-9. Model performance analysis for the gray balance of Kodak Q-60C target	104
FIG. 5.3-10. Model performance analysis for the hue shift of Kodak Q-60C target	105
FIG. 5.3-11. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (8-bit scan) for an independent Ektacolor paper target.	106
FIG. 5.3-12. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (8-bit scan) for independent Ektacolor paper target.	108
FIG. 5.4-1. Maximum reflectance of Fuji IT8.7/2 target.....	109
FIG. 5.4-2. Eigenvectors of Fuji IT8.7/2 target.....	112
FIG. 5.4-3. Histogram of the ΔE^*_{ab} from the tristimulus matching algorithm for Fuji IT8.7/2 target.....	113
FIG. 5.4-4. Example plots of the linearization process for Fuji IT8.7/2 target.....	116
FIG. 5.4-5. Concentration differences from the 3 by 11 model prediction (8-bit scan) against actual concentrations for Fuji IT8.7/2 target	119
FIG. 5.4-6. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (8-bit scan) for Fuji IT8.7/2 target.....	120
FIG. 5.4-7. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (8-bit scan) for Fuji IT8.7/2 target.....	121
FIG. 5.4-8. Model performance analysis for the gray balance of Fuji IT8.7/2 target.....	123
FIG. 5.4-9. Model performance analysis for the hue shift of Fuji IT8.7/2 target	123
FIG. 5.4-10. Histogram of the ΔE^*_{ab} error from the 3 by 11 model (12-bit scan) for an independent Fuji Ektachrome target	125
FIG. 5.4-11. Color difference versus L^* , C^*_{ab} and h_{ab} from the 3 by 11 model (8-bit scan) for an independent Fujicolor paper target.....	126

FIG. 5.4-12. Measured and predicted spectral reflectances of independent Fujicolor paper target.....	127
FIG. 5.4-13. Maximum reflectances of Fuji IT8.7/2 target and the independent Fujicolor target.....	128
FIG. 5.4-14. Rotated eigenvectors of the independent Fujicolor target and the Fuji IT8.7/2 target.	130

1. Introduction

In the graphic arts color reproduction process, a photographic original is captured by an analytical device and then recomposed by a synthetic medium from which forms the reproduction. A goal of the reproduction process is to make the reproduced color identical to the original when they are viewed side-by-side under a specific viewing condition. However, this goal is not always achieved satisfactorily due to the lack of processing accuracy. Therefore, an accurate input analytical device is a necessity in the reproduction system. The focus of this thesis is to colorimetrically characterize a desktop drum scanner serving as an analytical device in order to enhance the accuracy of graphic arts color reproduction.

In traditional printing, the scanning operation is done by a skilled craftsman using a "high-end" scanner . The scanner is usually in the million-dollar range and equipped with very sophisticated color correction controllers. Based on accumulated experience, the craftsman adjusts the controllers to convert the image density of the original to screen percentages of the separations for press printing. Since the craftsman has profound knowledge about how the screen density will translate into color-ink on paper, accurate color reproduction may be achieved in such a closed-loop environment.

Meanwhile, the color reproduction industry has experienced significant changes due to the advent of electronic image processing technology. The development of the desktop electronic scanner provides a more productive and less expensive method than traditional high-end scanning in color reproduction. Despite this technological advance, two issues need to be addressed first for the desktop system to become popular and successful.

The first issue is that the users of the desktop system do not always have good color separation skill compared with the printing craftsmen. Since the users of the desktop scanner are most likely artists with expertise not in offset printing, the desktop system has to provide a vehicle to assure the accuracy of the color reproduction. The second issue is that the reproduction synthetic medium may not be limited to ink on paper. Since the reproduction could be carried out in an open-ended system with additional different media such as CD ROM, CRT, film recorder, or digital color printer, the scanning operation designed for the close-looped ink-on-paper process is not adequate to assure accuracy of the color reproduction for open-ended media. Consequently, colorimetric accuracy independent from the output media is required for the desktop scanner to provide good color reproduction quality. Scanner colorimetric characterization is the first step in achieving device independent color for this open-ended color reproduction system and the scanner is also the first device in the color reproduction chain. Therefore, it becomes critical to have the scanning device colorimetrically characterized to record the image signal faithful to the original.

There are two general approaches in scanner colorimetric characterization: direct tristimulus value matching and spectral matching. Both approaches use the set of three digital counts from the three primary sensors in the scanner to derive requisite data. The direct tristimulus matching approach maps the digital counts to tristimulus values through a set of characterization functions. The spectral matching approach reconstructs the spectral data of the original by a spectral model and then calculates the tristimulus values with the standard color matching functions and an illuminant.

There have been several recent articles describing the colorimetric characterization of desktop scanners based on the tristimulus matching approach,¹⁻³ to be discussed in detail in the following chapter. A few articles have described the colorimetric characterization of desktop scanners based on the spectral matching approach.^{4,5} The tristimulus approach is easier to implement since it does not require a spectral analysis. However, the spectral match approach has not only the advantage of higher accuracy but also in functioning well under multiple illuminants and not being susceptible to problems of illuminant metamerism in comparison with the tristimulus matching approach. The spectral matching approach was chosen as the sole characterization method in this thesis.

The overall objective of this thesis was to achieve colorimetric characterization of a Howtek D4000 desktop drum scanner such that the scanner's output could be translated into accurate colorimetric signals of the target object. The scanner was treated as a densitometer where the scanner digital counts were related to the material's dye concentrations in order to reconstruct the spectral information of the photographic original. The spectral information was used to calculate tristimulus values and then CIELAB values as the final result of the characterization process. In a similar manner to current practice in the printing industry, photographic materials were used as the target objects. CIE illuminant D50 and the CIE 1931 2 degree standard colorimetric observer⁶ were used in all the computations as recommended by the Committee for Graphic Arts Technologies Standards (CGATS).⁷ The performance of the characterization method was evaluated quantitatively by ΔE^*_{ab} color differences between instrumental measurements and the characterized scanner output of the test targets. These results were also compared with previous efforts by other researchers.

2. Background

There have been several articles describing the colorimetric characterization of desktop scanners. In general, their methodologies can be categorized as operator intervention,⁸ polynomial regression,^{9,10} multidimensional interpolation,^{11,12} multi-channel analysis,^{13,14} and spectral model analysis.^{4,5} They all share one common goal: to achieve the smallest ΔE^*_{ab} difference between the original and the transformed digital signals.

Ideally, this goal could be achieved easily with a simple 3 by 3 matrix if the scanner's sensor spectral sensitivities are a linear combination of a set of CIE color matching functions. This has been proven mathematically by Schrödinger¹⁵ that in transforming from one set of primaries to another set of primaries, the new primaries will be homogeneous linear functions of the old primaries. This topic was revisited recently by Gordon and Holub.¹⁶ Gordon and Holub also cautioned that if the sensors' sensitivities are not linear combinations of color matching functions, nonlinear transformations are needed to relate the RGB digital counts to XYZ tristimulus values. This is the typical case.

Wandell and Farrell⁸ utilized the 3 by 3 transformation and also analyzed the residual distribution between the measured and predicted tristimulus values. They found that the error cloud was principally scattered in one direction and proposed to add a fourth channel along the color coordinates where most of the characterization error was observed. By visually evaluating images, the user could use a slider to correct the estimated color and to reduce the transformation error. In their experiment, the characterization results of a HP Scanjet IIC with a Macbeth color checker yielded an average ΔE^*_{ab} of 3.6 (maximum of

13.2) for the direct 3 by 3 transformation and improved to an average ΔE^*_{ab} of 1.7 (maximum at 6.2) with user intervention along the fourth dimension. The operation of user intervention did improve the color accuracy; however, it added considerable burden on the desktop user for extra color adjustment likely reducing production speed.

The 3 by 3 transformation failed to relate the scanner digital counts to tristimulus values because the scanner responsivities were not a linear combination of CIE color matching functions. One could ask the question: why not build a scanner having responsivities that are a linear combination of CIE color matching functions? Vrhel and Trussell have addressed this question by deriving a method to select color filters and imaging illuminants for scanner systems.¹³ A vector space approach combined with set theoretical methods was used to synthesize the desired filters with as few basis filters as possible.¹⁴ Optimal nonnegative sets of filters were derived by this method for several viewing illuminants. Simulations were performed on 343 spectral reflectance patches from a color copier. The simulation results under illuminant D65 were as follows: average ΔE^*_{ab} of 2.3 unit (maximum of 10.7) for the optimal 3 filters, average ΔE^*_{ab} of 0.35 unit (maximum of 1.3) for the optimal 4 filters, average ΔE^*_{ab} of 0.34 unit (maximum of 1.4) for the optimal 5 filters. The constraint of nonnegative terms for the filters' spectral response would ensure that the filters are physically conceivable. However these results were all from computer simulation; it is not clear that how feasible it is to manufacture such filter sets with good signal-to-noise performance and with reasonable cost from commercially available filter materials.

Without the luxury of rebuilding a new scanner system, researchers and engineers are trying to characterize the existing scanner system with empirical approaches like

polynomial regression or multi-dimensional interpolation. The technique of polynomial regression¹⁷ is based on the following theory: assuming the processing error in the scanning elements follows a normal distribution, a regression equation can be established to represent the relationship between the predictor variables - RGB digital counts and the response variables - their corresponding XYZ values. North⁹ performed stepwise polynomial regression for a Sharp JX450 flat-bed scanner with 125 color patches of photographic material and achieved results where 86% of the predictions were less than 2.0 ΔE^*_{ab} . Berns¹⁰ performed stepwise polynomial regression with 200 photographic samples based on photographing a Munsell Book of Color and achieved an average ΔE^*_{ab} of 1.6 units (maximum at 4.5) for illuminant D50. Kang² performed polynomial regression for a Sharp JX450 scanner using a Kodak Q60C photographic standard and achieved an average ΔE^*_{ab} of 2.8 for a 3 by 3 matrix, an average ΔE^*_{ab} of 2.5 for a 3 by 6 matrix and an average ΔE^*_{ab} of 1.9 for a 3 by 14 matrix. More results are listed in Table I. Kang also included a gray balance routine in his implementation, which forced the gray patches to have equal amount of RGB digital counts.

Berns³ further concentrated on the color correction operation of the system and performed a regression from the digital counts directly to CIELAB values. The characterization was performed on a Sharp JX610 scanner with a Kodak Q60C reflectance target and a Macbeth Color Checker chart; the result was an average ΔE^*_{ab} of 1.8 (maximum at 8.8) for a 3 by 9 matrix. Other than using the Kodak Q60C as a test target, Clippeleer¹⁸ applied polynomial regression on a flatbed CCD scanner with an Agfachrome IT8.7/1 standard and achieved an average ΔE^*_{ab} around 2.5 (maximum at around 9.0) for a 3 by 3 matrix, around 2.0 (maximum at around 9.5) for a 3 by 8 matrix, around 1.5

(maximum at around 5.0) for a 3 by 27 matrix and around 1.0 (maximum at around 3.5) for a 3 by 64 matrix.

Several issues exist when using the regression technique. One is the regression function can not be extrapolated beyond the range of the known predictor variables. Another issue is how to interpret any physical meaning for the non-linear polynomial terms. Moreover, it is very difficult to calculate the inverse transformation from a high-order polynomial regression function. Fortunately, this is not required in this application. Multidimensional interpolation techniques with table look up were then considered as another approach to scanner characterization.^{11,19}

The idea of multi-dimensional interpolation is based on the mathematical principle that any smooth function can be approximated by many contiguous linear segments. Together, all the small linear segments define the system response characteristic between the input domain and the output domain. Treating a scanner as a black box, the input/output relationship can be characterized between the system input (scanner values) and the system output (tristimulus values) with a look-up table by the interpolation technique.

There are several ways to subdivide the domain space into subspaces. Two typical ways are cubic subspace division and tetrahedral division. The cubic interpolation technique uses eight corners of a cube to interpolate between two 3-dimensional spaces. It is a straight-forward operation to map a uniform orthogonal cube in six flat plans to another solid form having eight corners in another space. However inversely, any eight random corners may form more than six flat plans; therefore, there is great difficulty to perform the inverse mapping in cubic subspace, especially a subspace that may be concave.

The tetrahedral interpolation technique is based on the phenomenon that four points define a unique tetrahedron. Consequently, a subcube divided into tetrahedrons in one color space can be linearly related to a point in the corresponding tetrahedron in the other color space and the forward or inverse relationship is a unique one-to-one mapping. Hung¹¹ applied tetrahedral interpolation and LUT technique (33x33x33) to characterize a Sharp JX450 scanner with 125 photographic color patches for illuminant D65 and resulted in an average ΔE^*_{ab} of 1.1 with a maximum error of 9.9. For comparison, Hung also applied polynomial regression on the same configuration and got an average ΔE^*_{ab} of 4.7 (maximum at 12.9) for 1st order regression, 2.8 (maximum at 8.2) for 2nd order regression and 2.2 (maximum at 7.8) for 3rd order regression.

To compare the performance difference between various LUT sizes, Hung¹² used an analytical model to generate 65x65x65 data points and tested the data with 5x5x5, 9x9x9, 17x17x17 and 33x33x33 linear tetrahedral LUT. In the case of Beer's law simulation, the average ΔE^*_{uv} errors were 5.4, 1.4, 0.4 and 0.1 for 5x5x5, 9x9x9, 17x17x17 and 33x33x33 tetrahedral LUTs, respectively. The maximum ΔE^*_{uv} errors were 18.7, 6.0, 1.7 and 0.5 respectively. Hung suggested that the suitable size for a LUT model showing a small enough error may result from 17x17x17 to 33x33x33 look-up tables. However, a 17x17x17 LUT implies 4913 measurements in each of the input and output domains.

Hung¹² had further combined the tetrahedral and LUT technique with nonlinear interpolation. He adjusted the RGB digital counts with "tone curve adjustment" using one-dimensional LUTs similar to the gray balance routine Kang used. The results of this technique (5*5*5 LUT) depicted ΔE^*_{uv} error of 0.3 (maximum at 2.1) for 33x33x33

simulated test data based on Beer's law model. Under the same condition, the regression technique resulted ΔE^*_{uv} error of 15.1 (maximum at 52.3) for 1st order regression, ΔE^*_{uv} of 5.5 (maximum at 29.4) for 2nd order regression and ΔE^*_{uv} of 2.1 (maximum at 8.8) for 3rd order regression respectively. From these results, it seemed that the non-linear one-dimensional interpolation combined with multi-dimensional tetrahedral linear interpolation produced a better result than the regression method. Unfortunately, these test results were not available in ΔE^*_{ab} ; neither has there been any further published results on scanner characterization using this technique.

Rodriguez and Stockham⁴ proposed a method which treats the digital counts of the scanner output as the scanner density readings and relates them directly to colorimetric quantities based on the assumptions that the system responsivities of the scanner are narrow, like delta functions, and the spectral characterization of the scanned photographic material is known. They used Newton's method to estimate the dye densities of each color patch with the transparent film's spectral characterizations of the dye according to Beer's law. Beer's law^{20,21} states that the density spectrum of a color patch is linearly related to the concentrations of the dyes and its spectral transmittance can be reconstructed with the density spectrum as following:

$$K(\lambda) = k_0(\lambda) + C_1 k_1(\lambda) + C_2 k_2(\lambda) + C_3 k_3(\lambda) + \dots + C_n k_n(\lambda)$$

$$T(\lambda) = I(\lambda) / I_0(\lambda) = e^{-K(\lambda)}$$

where $k_0(\lambda)$ is the spectral density of the base and $k_n(\lambda)$ is the unit absorptivity spectrum of the nth dye in the material. C_n is the associated concentration of each nth dye. $I_0(\lambda)$ is the incident light and $I(\lambda)$ is the transmitted light. $T(\lambda)$ is the relative spectral transmittance

factor. For a photographic material, the scanner's digital counts can be related to the concentrations of the cyan, magenta and yellow dyes and then the spectral information as well as the tristimulus values can be calculated accordingly. More detail about Beer's law is discussed in the following chapter.

Rodriguez and Stockham applied the spectral method for a Hell 3000 series drum scanner with a Kodak Ektachrome Q-60 test target. An iterative method was used to estimate the dye concentrations from the scanner densities.^{4,22} With the Ektachrome dye spectral density curves provided by the manufacturer, the estimated concentrations were used to reconstruct the estimated spectrum based on Beer's law. The estimated spectrum was fed into scanner model equations to generate the predicted scanner densities. The scanner model equations were based on the physical channel responsivities of the graphic arts scanner. The difference between the predicted scanner densities and the actual scanned density readings was used to calculate the increment of the estimated concentrations. The iterative algorithm was based on the theory that when the concentrations are correctly estimated, the estimated spectrum would be identical to the actual spectrum, therefore, the difference between the estimated and actual scanner densities would be negligible and the iteration can be ended. Note that this iteration criterion was not based on CIE colorimetry and the spectral density of the base, $k_0(\lambda)$, was not involved in the computation. They achieved the characterization for average ΔE^*_{ab} less than 2 and maximum values of less than 4.

Viggiano and Wang⁵ applied the Bouguer-Lambert-Beer model to calibrate a flat bed scanner with a Kodak Ektachrome Q60C target. They performed an extensive analysis to compensate for the scanner's nonlinear amplitude response function. The amplitude

response, sometimes referred to as "gamma correction," was incorporated by the scanner manufacturer to account for the nonlinearity introduced by CRTs. As a result, the amplitude response function should be compensated when getting the actual sensor readings of the object density from the scanner output. They used a non-linear function to model the amplitude response function of a series of spectrally non-selective tiles. In addition, they performed a principal component analysis on the density spectra of all the patches to obtain the spectral curves of the dye set rather than using data supplied by the manufacturer. An ordinary least-squares algorithm was used in predicting each patch's concentrations with the derived eigenvectors from the principal component analysis. The published characterization results were an average ΔE^*_{ab} of 4.1 and a 90th percentile of 6.2. Besides the procedural difference in estimating the concentrations (least-squares algorithm versus iterative algorithm), the fact that Viggiano and Wang performed their experiment on a flat-bed CCD scanner while Rodriguez and Stockham used a high-end drum scanner contributed to the large performance difference.

At the current state-of-the-art, all these published characterization results as summarized in Table I are still in the range of average errors larger than 1 ΔE^*_{ab} unit with the maximum errors larger than 3 ΔE^*_{ab} units. Stokes, et al²³ found that the perceptibility threshold for images is around 2 ΔE^*_{ab} units on average. Therefore, to have the colorimetric error introduced by the scanning operation not to be perceptible, it requires the maximum characterization error of the scanner to be around 2 ΔE^*_{ab} units. Meanwhile, since the scanner operation is the first element in the color reproduction chain, it is desirable to keep the average characterization error as small as possible to prevent the error from propagating and amplifying through following reproduction stages. The fundamental goal

of this thesis was to achieve higher characterization accuracy than the published results summarized in Table I.

TABLE I. List of published scanner characterization results.

Method	Author	Avg. ΔE^*_{ab}	Max. ΔE^*_{ab}
3 by 3	Wandell and Farrell ⁸	4.9	13.6
3 by 3	Wandell and Farrell ⁸	3.6	13.1
3 by (3 + 1)	Wandell and Farrell ⁸	2.4	6.2
3 by (3 + 1)	Wandell and Farrell ⁸	1.7	6.2
3 simulated filters	Vrhel and Trussell ¹³	2.3	10.7
4 simulated filters	Vrhel and Trussell ¹³	0.4	1.3
5 simulated filters	Vrhel and Trussell ¹³	0.3	1.4
Stepwise Polynomial	North ⁹	2	N. A.
3 by 3 + Gray Balance	Kang ²	2.8	N. A.
3 by 6 + Gray Balance	Kang ²	2.5	15
3 by 14 + Gray Balance	Kang ²	1.9	N. A.
1st order reg.	Hung ¹¹	4.7	12.9
2nd order reg.	Hung ¹¹	2.8	8.2
3rd order reg.	Hung ¹¹	2.2	7.8
5*5*5 LUT	Hung ¹¹	1.1	9.9
3 by 6 (SS XYZ)	Berns ³	3.6	22.1
3 by 9 (SS XYZ)	Berns ³	2.5	12.5
3 by 9 (SS Lab)	Berns ³	1.8	8.8
3 by 9 (SS .33)	Berns ³	2.4	9.2
3 by 3 Polynomial	Clippeeler ¹¹	2.5	9.0
3 by 8 Polynomial	Clippeeler ¹¹	2.0	9.5
3 by 27 Polynomial	Clippeeler ¹¹	1.5	5.0
3 by 64 Polynomial	Clippeeler ¹¹	1.0	3.5
Spectral model	Viggiano and Wang ⁵	4.1	6.2(90%)
Spectral model	Rodriguez and Stockham ⁴	< 2	< 4

3. Scanner Characterization Process

In the graphic arts color reproduction process, photographic materials are presented as the original. The scanner characterization method in this thesis utilizes the colorimetric and spectral properties of the photographic material to form the basis for characterizing the original. An analytical method is used in material analysis to decompose the spectral information of the target material into unit absorptivities of the primary dyes. The scanner is treated as an imaging densitometer enabling the relationship from the scanner readings by the scanner to the dye concentrations of the target material to be modeled. This model is then used to predict the dye concentrations from the scanner's digital readings for images having the same dye set. The predicted concentrations can be used to recompose the spectral data with the unit absorptivities of the dyes. The spectral data is finally used to calculate colorimetric parameters of the original for defined observers and illuminant. Color differences can be assessed between the measured and the predicted colorimetric data to evaluate the model performance. An object-oriented representation of the data flow is shown in Fig. 3-1. To have an objective performance verification, an independent original of the same material will be used as the testing set to verify the model performance.

FIG. 3-1. Overall data flow of the characterization method.

3.1 Material Analysis

There are two general types of photographic materials: transparent and opaque. As shown in Fig. 3.1-1, the optical property of the material determines its viewing and measurement conditions. The transparent material is viewed and measured with 0/0 geometry. The opaque material is viewed and measured with d/0 geometry. Hence, there are different spectral models for each kind of material based on the Beer-Bouguer theory^{20,21} and the Kubelka-Munk theory,^{20,24-26} respectively.

FIG. 3.1-1. Optical geometry of transmittance and opaque materials.

3.1.1 Spectral Model - Transparent Material

The Beer-Bouguer theory^{20,21} states that the intensity of a beam of monochromatic light i passing through a transparent material of thickness X suffers a weakening of intensity, di , that is proportional to its intensity:

$$di / dx = - K i , \quad (1)$$

where K is the absorption coefficient of the material. Integration of this differential equation over the entire thickness of the material gives

$$\ln(I / I_0) = \ln(T_i) = -K X , \quad (2)$$

or

$$I / I_0 = T_i = e^{-KX} , \quad (3)$$

where I_0 is the intensity of the monochromatic light before passing through the material; after passing through it is I . T_i is the internal transmittance of the material.

For material with n layers of different colorants with a single base substrate, the total absorption, K , of unit thickness X becomes:

$$K = k_t + K_1 + K_2 + \dots + K_n, \quad (4)$$

where k_t is the absorption of the substrate without colorant, and $K_1, \dots, K_n$ are their respective absorptions of n colorants. With the further assumption that the unit spectral absorption properties of each dye are invariant with concentration, Eq. (4) becomes:

$$K = k_t + c_1 k_1 + c_2 k_2 + \dots + c_n k_n, \quad (5)$$

where k_t is the absorption of the substrate without colorant, $c_1, \dots, c_n$ are scalars representing amount of the concentrations of the various colorants, and $k_1, \dots, k_n$ are their respective unit absorption coefficients. Further expanding the domain from monochromatic light to chromatic light, variables T , I_0 , I and K become functions of wavelength (λ) as follow:

$$\begin{aligned} I/I_0(\lambda) &= T_i(\lambda) \\ &= e^{-(k_t(\lambda) + c_1 k_1(\lambda) + c_2 k_2(\lambda) + \dots + c_n k_n(\lambda))}, \end{aligned} \quad (6)$$

Equation (6) forms the basis of the spectral analysis for transparent materials.

Since only photographic materials are presented as the original, several assumptions are made specifically about this material in order to be applicable to the Beer-Bouguer theory:²⁷

- No optical scattering,
- No fluorescence,
- Refractive index discontinuity between material and air is not significantly influenced by the variation of the dye concentrations.

The reversal film after processing can be considered as a transparent medium consisting of cyan, magenta and yellow dyes coated on a base gelatin. According to Beer-Bouguer theory and the previous stated assumptions, the internal transmittance of a reversal film can be described as follow:

$$T_i(\lambda) = e^{-(k_g(\lambda) + c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda))}, \quad (7)$$

$$= e^{-k_g(\lambda)} * e^{-(c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda))}, \quad (8)$$

where c_c , c_m and c_y are the concentrations and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are the unit spectral absorptivities of cyan, magenta and yellow dye, respectively. $k_g(\lambda)$ is the spectral absorptivity of the base and can be separated out as the base transmittance, $T_g(\lambda)$. Assuming the change of refractive index between the base material and air is not influenced by different amount of dye concentration, the measurement of $T_g(\lambda)$ would be the net base transmittance including the refraction factor. The total transmittance of the transparent film becomes:

$$T(\lambda) = T_g(\lambda) * e^{-(c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda))}, \quad (9)$$

Further dividing $T_g(\lambda)$ and applying the natural logarithm function on both sides of Eq. (9):

$$K(\lambda) = -\ln(T(\lambda) / T_g(\lambda)) = c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda). \quad (10)$$

Consequently, any given spectral transmittance of a color on the film can be decomposed into a linear combination of the dye concentrations and its respective unit absorptivity.

3.1.2 Spectral Model - Opaque Material

The most common photographic reflectance material is photographic paper, which has transparent dye layered on top of a paper base. The dye layer is considered as a homogeneous layer of finite thickness. Scattering occurs within the natural fiber paper base. Even though the paper base is not opaque, by backing the paper with black material as recommended by CGATS.5-1993 standard,⁷ the measurement of the paper base is equivalent to the measurement of a medium that is thick enough to be opaque. As a result, the photographic paper is considered as a transparent dye layer in optical contact with a scattering, opaque support. This has been described in detail by Berns.²⁸

Kubelka and Munk²⁴ described the relationship between reflectance (R) and the proportionality constant of absorption coefficient (K) over scattering coefficient (S) of a colored layer of finite thickness (X) applied on a background of known reflectance (R_g) as shown in Eq. 11.

$$R = \frac{1 - R_g(a - b \coth(bSX))}{a - R_g + b \coth(bSX)}, \quad (11)$$

where $a = 1 + (K/S)$ and $b = (a^2 - 1)^{1/2}$. The symbol "coth" is the hyperbolic cotangent function and is defined as $\coth(bSX) = [\exp(bSX) + \exp(-bSX)] / [\exp(bSX) - \exp(-bSX)]$. For opaque materials, the thickness X is large enough to make the $\exp(-bSX)$ negligible compared to $\exp(bSX)$. Eq. (11) can then be simplified as:

$$R_\infty = 1 + (K/S) [(K/S)^2 + 2(K/S)]^{1/2}, \quad (12)$$

Since only photographic paper is presented as the original, several assumptions are made specifically about the opaque material in order to be applicable to the Kubelka-Munk theory as follows:

- No fluorescence,
- The scatter effect caused by the dye is negligible,
- Refractive index discontinuity between material and air is not significantly influenced by the variation of the dye concentrations.

When assuming the scattering coefficient S in the dye layer is allowed to approach zero, Eq. (11) becomes:

$$R = R_g e^{-2KX}, \quad (13)$$

which is very similar to Eq. (3) describing the Beer-Bouguer theory. However, it is noted that the Beer-Bouguer theory is defined for collimated light (0/0 geometry) while the Kubelka-Munk theory is defined for diffused light (d/d geometry).^{20,27} Since the R_g is measured on the finished paper base with minimum dye concentration, the influence of the refractive index discontinuity between the paper and the air would be built into the R_g measurement automatically. In addition, the thickness term X in Eq. (13) can be eliminated since it is constant for given photographic paper. The spectral absorption of the dyes, $K(\lambda)$, is derived as a function of spectral reflectance factor by the inverse of Eq. (13) as follow:

$$K(\lambda) = -0.5 \ln (R(\lambda) / R_g(\lambda)) , \quad (14)$$

Given that the photographic paper is a continuous-tone material, it is assumed that the absorption properties of a given area are the sum of the absorption properties of each of the cyan, magenta and yellow dyes:

$$K_{\text{mixture}}(\lambda) = K_c(\lambda) + K_m(\lambda) + K_y(\lambda) , \quad (15)$$

With further assumption that the unit spectral absorption properties of the dyes are invariant with concentration, Eq. (15) becomes:

$$K(\lambda) = c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda) , \quad (16)$$

where c_c , c_m , c_y are scalars representing amount of the concentration of cyan, magenta and yellow dye respectively, and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are their respective unit absorption coefficients. Combining Eq. (14) and Eq. (16) together, the spectral reflectance data can be directly related to the linear combination of the dye concentrations and their respective unit absorptivities, as follows:

$$-0.5 \ln(R(\lambda) / R_g(\lambda)) = c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda) , \quad (17)$$

or

$$R(\lambda) = R_g(\lambda) * e^{-2(c_c k_c(\lambda) + c_m k_m(\lambda) + c_y k_y(\lambda))} . \quad (18)$$

Eq. (17) forms the basis of the spectral analysis for opaque photographic materials.

3.1.3 Derivation of Unit Absorptivities

The fact that the spectral data of every color on the photographic material can be transformed into a linear combination of its primary dyes' absorptivities and its respective

concentration provides a firm basis for statistical analysis. Principal component analysis is concerned with explaining the variance-covariance structure through a few linear combination of the original variables (or eigenvectors).²⁹ Consequently, the primary dyes' absorptivities of the material are essentially the eigenvectors and the concentrations of the dyes are the respective scalar for each variable in the linear combination.

When a sampling population is uniformly distributed for a photographic material's color gamut, the eigenvectors from the principal component analysis would depict the variation vectors among all the samplings from their mean. Ideally, these "global" eigenvectors should resemble the primary dyes' absorptivities since what makes the color different is just the concentration differences of the unique dyes in the material. However, principal component analysis traditionally tends to draw maximum explanation of the variation of the first eigenvector before further deriving consequent eigenvectors; there is no guarantee that all the primary dyes will be treated equally in deriving the eigenvectors.

Fortunately, there are rotation options^{29,30} available in several statistical software packages. One particular option is "equamax rotation", which equalizes the variance between each eigenvector. However as indicated by Berns,²⁷ there is significant unwanted secondary absorptions in the global eigenvectors, which may be introduced by the "equamax rotation" to compensate the uneven sampling of the color gamut. As a result, further correction is needed. Separate analyses are performed to estimate each dye's eigenvector (and hopefully its absorptivity) one at a time, by sampling along one single primary with a minimum presence of other primaries. These three "local" eigenvectors form the basis axes of the primary dyes. However due to differences between the

theoretical spectral models and actual behavior, these local eigenvectors do not represent the global variation for the entire gamut population.

A combined method was used by Berns²⁷ where the global eigenvectors were rotated to match the local eigenvectors minimizing sum of squares error. Since the local eigenvectors are defined by the primaries individually, the rotation from the global eigenvectors to the local eigenvectors removes the unwanted secondary absorption while preserving the representation of the global variation. Multiple linear regression¹⁷ can be used:

$$\begin{aligned}\mathbf{b} &= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \\ \hat{\mathbf{Y}} &= \mathbf{X} \mathbf{b}\end{aligned}\tag{19}$$

where the $\mathbf{Y}$ matrix contains the three local eigenvectors and the $\mathbf{X}$ matrix contains the three global eigenvectors. The 3*3 $\mathbf{b}$ matrix is the rotation coefficients from the regression analyses and the estimated matrix $\hat{\mathbf{Y}}$ are the resulting final eigenvectors to describe the absorptivities of the primary dyes.

3.2 Prediction of Actual Concentrations

An analytical method was used to determine the concentrations needed to colorimetrically match each color. This type of method is commonly referred to as computer colorant formulation and has been long used in the paint matching industry with satisfactory results.^{20,24,31} This analytical method estimates the concentration mixture of the colorants with a numerical computation algorithm until the predicted and actual tristimulus values are within a specified goodness level.

Allen²⁰ has described a tristimulus matching algorithm for matching opaque samples or clear samples based on a pseudotrstimulus match and Newton-Raphson iteration. In Allen's algorithm, it first estimates initial concentrations by:

$$\mathbf{c} = (\mathbf{WD}\Phi)^{-1} \mathbf{W}\mathbf{D}\mathbf{f} , \quad (20)$$

where $\mathbf{c}$ is the scalar matrix of the colorants; in this thesis, c_c , c_m and c_y are scalars of concentration to each of the cyan, magenta and yellow dye unit absorptivities as

$$\mathbf{c} = \begin{bmatrix} c_c \\ c_m \\ c_y \end{bmatrix} , \quad (21)$$

W_x , W_y and W_z are the ASTM tristimulus weights⁷ for a given CIE observer and illuminant combination:

$$\mathbf{W} = \begin{bmatrix} W_x(\lambda_1) & \dots & W_x(\lambda_n) \\ W_y(\lambda_1) & \dots & W_y(\lambda_n) \\ W_z(\lambda_1) & \dots & W_z(\lambda_n) \end{bmatrix} , \quad (22)$$

$\mathbf{D}$ is the multiple-linear regression weighting matrix, which is the partial derivative of reflectance or transmittance with respect to absorption for opaque or transparent materials:

$$\mathbf{D} = \begin{bmatrix} d(\lambda_1) & 0 & \dots & 0 \\ 0 & d(\lambda_2) & \dots & 0 \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ 0 & 0 & \dots & d(\lambda_n) \end{bmatrix} , \quad (23)$$

Φ is the matrix of unit spectral absorptivities $k(\lambda)$ for each cyan, magenta and yellow dye and n equals the number of wavelengths as

$$\Phi = \begin{bmatrix} k_c(\lambda_1) & k_m(\lambda_1) & k_y(\lambda_1) \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ k_c(\lambda_n) & k_m(\lambda_n) & k_y(\lambda_n) \end{bmatrix}, \quad (24)$$

$\mathbf{f}$ is the given spectral absorptivity $K(\lambda)$ of a standard color. In this thesis, $\mathbf{f}$ is calculated from the spectral measurement of each color by Eq. (14) for opaque materials or by Eq. (10) for transparent materials:

$$\mathbf{f} = \begin{bmatrix} K_{\text{standard}}(\lambda_1) \\ \cdot \\ \cdot \\ \cdot \\ K_{\text{standard}}(\lambda_n) \end{bmatrix}. \quad (25)$$

The first estimation of the concentrations (Eq. 20) are used to calculate the spectral data and then tristimulus values. Subsequent iterations by means of the Newton-Raphson method can improve the prediction results toward a closer match and stop the iteration when the tristimulus difference have become smaller than some goodness parameter. The iteration algorithm is:

$$\begin{bmatrix} \Delta c_c \\ \Delta c_m \\ \Delta c_y \end{bmatrix} = (\mathbf{W}\mathbf{D}\Phi)^{-1} \begin{bmatrix} \Delta X \\ \Delta Y \\ \Delta Z \end{bmatrix}, \quad (26)$$

$$\mathbf{c} = \begin{bmatrix} c_c + \Delta c_c \\ c_m + \Delta c_m \\ c_y + \Delta c_y \end{bmatrix}. \quad (27)$$

The goodness parameter in this thesis was set as follows:

$$\left[(\Delta X)^2 + (\Delta Y)^2 + (\Delta Z)^2 \right]^{1/2} \leq 0.001 , \quad (28)$$

where the perfect reflectance diffuser has a Y equal to 100.

Similar tristimulus matching algorithms were proposed by Ohta.^{32,33} except that his algorithm does not require spectral data of the standard. Both Allen's and Ohta's algorithm can be traced back to the pioneering work of Park and Stearns.³⁴ Lately, Berns²⁷ has applied Allen's algorithm in predicting the dye concentrations of thermal transfer paper with good results.

3.3 Building Characterization Model

The key issue in building the characterization model is how to relate the scanner output to the actual concentrations. With the primary dyes' absorptivities, each color's spectral distribution can be first decomposed into the concentrations of the primary dyes by the tristimulus matching algorithm. If the scanner's sensor spectral responsivities are very narrow, the natural logarithm of the scanner's digital count readings can be related from the integral density³⁵ to the analytic densities of the material's at the specific wavelength as follow:

$$-\ln\left(\int_{\lambda}^{\lambda+d\lambda} T(\lambda) \cdot S(\lambda) \cdot s(\lambda) d\lambda\right) = -\ln(T(\lambda) \cdot S(\lambda) \cdot s(\lambda) \int_{\lambda}^{\lambda+d\lambda} d\lambda) , \quad (29)$$

where $T(\lambda)$ is the spectral transmittance or reflectance of the object property received by the scanner sensor; $S(\lambda)$ is the spectral property of the light source; $s(\lambda)$ is the scanner sensor

responsivity. The integral of the product of $T(\lambda)$, $s(\lambda)$ and $S(\lambda)$ is actually the scanner channel reading.

When the bandwidth $d\lambda$ is very small, $T(\lambda)$, $s(\lambda)$ and $S(\lambda)$ are not changed with the variance of λ . Since $T(\lambda)$, $s(\lambda)$ and $S(\lambda)$ are constant terms in the integral, they can be moved outside the integral and Eq. (29) becomes valid. As described in Eq. (2) and Eq. (5), the $-\ln(T(\lambda))$ is actually the total absorption $K(\lambda)$, which is a linear combination of the products of each primary dye's concentration with its unit absorptivity. As a result, after applying the natural logarithm transformation on the scanner digital counts, these transformed digital values are directly related to the dye concentrations of the primary dyes. From this correlation, a training model can be derived to relate the scanner digital counts to the material's concentrations. However in reality, the scanner sensor responsivities may not be narrow enough such that the integral interval $d\lambda$ is wider and $T(\lambda)$, $s(\lambda)$ and $S(\lambda)$ are not constants in the integral. Consequently, Eq. (29) does not hold and non-linear functions are needed to describe the relationship between the integral density and the analytic densities.

Two steps are taken to derive the characterization model. The first step is to linearize the scanner digital counts to the concentrations of the spectrally non-selective colors. The second step is to relate the linearized digital values to the concentrations of all colors considering the possible cross-talk between the scanner's channel responsivities. Combining these two steps together, the scanner digital counts can be translated into the concentrations of the target material.

3.3.1 Linearizing Scanner Signals

The purpose of the linearization process is to independently relate the red, green and blue digital counts to respective cyan, magenta and yellow concentrations. This can be achieved by regressing the scanner readings with the respective concentrations of the non-selective colors. However, the red, green and blue scanner readings (denoted d_r , d_g and d_b) are not always linearly related to the material's concentrations. Fig. 3.3-1 is an example plot of the scanner sensor readings (normalized between 0 and 1) against the concentrations of a group of spectrally non-selective colors.

FIG. 3.3-1. Plots of normalized scanner readings against concentration readings for spectrally non-selective colors.

It is clear that a transformation function is needed to linearize the scanner readings with the material concentrations. Stepwise polynomial regression can be used to derive the linearization function as:

$$\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y},$$

$$\hat{D} = [\beta_0 \quad \beta_1 \quad \beta_2 \quad \beta_3 \quad \beta_4 \quad \beta_5] \cdot [1 \quad N_d^1 \quad N_d^2 \quad N_d^3 \quad N_d^4 \quad N_d^5]^T. \quad (30)$$

where $\mathbf{X}$ is the 5th order matrix of N_d and N_d is the normalized scanner digital count in natural log transformation. $\mathbf{Y}$ is the concentration matrix of spectrally non-selective colors. $\hat{D}$ is the predicted linearized digital count. Note that β_0 term is needed to model the possible dark current in the scanner system.

3.3.2 Relating Scanner Readings to Concentration

Ideally, if the scanner's sensor responsivities are narrow enough, the scanner's readings would be the linear combinations of the dyes' concentrations. After the scanner digital counts are transformed through the linearization process, a simple 3 by 3 transformation should be able to relate the transformed digital values to the actual dye concentrations as follow:

$$\beta = (\mathbf{D}^T \mathbf{D})^{-1} \mathbf{D}^T \mathbf{C},$$

$$\begin{bmatrix} \hat{C}_c \\ \hat{C}_m \\ \hat{C}_y \end{bmatrix} = \begin{bmatrix} \beta_{cr} & \beta_{cg} & \beta_{cb} \\ \beta_{mr} & \beta_{mg} & \beta_{mb} \\ \beta_{yr} & \beta_{yg} & \beta_{yb} \end{bmatrix} \cdot \begin{bmatrix} D_r \\ D_g \\ D_b \end{bmatrix}, \quad (31)$$

where the β terms are derived by regression. D_r , D_g and D_b are the transformed red, green and blue scanner readings. $\hat{C}_c$, $\hat{C}_m$ and $\hat{C}_y$ are the predicted cyan, magenta and yellow concentrations of the target material.

However in reality, the scanner's channel responsivities are not always narrow enough to be totally linearly independent. Unwanted cross-talk could exist between the scanner's channel responsivities. Stepwise regression with higher order polynomial equation is used to model the non-linear relation between the transformed digital values and the material concentration including the cross-talk. Second order polynomial terms plus $r*g*b$ cross term are often used in the model. The model coefficients for each independent variable in a matrix form is as follows:

$$\beta = [\beta_0 \quad \beta_r \quad \beta_g \quad \beta_b \quad \beta_{r*g} \quad \beta_{r*b} \quad \beta_{g*b} \quad \beta_{r*r} \quad \beta_{g*g} \quad \beta_{b*b} \quad \beta_{r*b*g}].$$

Following the stepwise selection, some of these coefficients will equal zero.

3.4 Model Verification

Now that the scanner digital counts can be translated into the dye concentrations by the characterization model, it is possible to reconstruct the spectral data of each object color with the unit absorptivities of corresponding dyes by Eq. (9) or Eq. (18) described in the material analysis section. With the reconstructed spectral data, the model-predicted colorimetric properties of the target material can be compared with the instrument-measured data. CIELAB color differences can be generated to assess the model performance. The complete process flow of the characterization method is summarized by the solid arrow lines in Fig. 3.4-1.

Throughout the derivation of the characterization model, the spectral data measurement, the material analysis, and the scanning operation are all done on the same target object. It is done so as to provide a consistent ground for the model training process. However in real-life applications, a characterized device has to work well with independent data. Consequently, an independent object of the same photographic material was processed through this characterized scanner system. The colorimetric information generated by the scanner system is compared with the measured colorimetric information of the independent test target. This colorimetric difference data shall serve as the most objective way in verifying the model performance. The process flow of the independent verification is shown in the dotted lines in Fig. 3.4-1.

FIG. 3.4-1. Flow chart of the characterization process.

3.5 Comparison with prior spectral methods

The main resemblance between the scanner characterization method of this thesis and prior spectral methods (Viggiano and Wang,⁵ Rodriguez and Stockham,^{4,22}) is the use of spectral models. However, there are several major fundamental differences. Viggiano and Wang used the results from a principal component analysis of the global density spectra as the material's unit absorptivities with which the concentrations were estimated with a general least-square algorithm. Rodriguez and Stockham used manufacturer provided spectral absorptivities and applied an iterative method based on the matching of the scanner density readings to predict the actual concentrations. The characterization method in this thesis derived the unit absorptivities with the global and the ramp spectral data of the actual target and the prediction of the concentrations is based on an iteration method with the tristimulus matching algorithm, which guarantees a true visual match. These different methods result in different model performance.

4. Experimental

4.1 Target Objects

Both opaque and transparent materials were selected as the target objects in this thesis. As described by McDowell,³⁶ since the color reproduction in the graphic arts industry is mostly based on several types of photographic materials, it is then possible to define the spectral range of the reproduction color with several particular dye sets among the photographic materials. Based on this characteristic, ANSI/IT8 committee has completed two standards IT8.7/1 and IT8.7/2 for input scanner calibration with transparent films and photographic paper products, respectively. Since these IT8.7 targets are becoming the industrial standard reference in device characterization, they were consequently adopted as the target objects for building the characterization models.

There are certain limitations when using these the IT8 targets. One is the gray balance of the neutral colors. Since the colors on the IT8 target are composed by three spectrally selective dyes, not a single spectrally neutral dye, any minute off-balance among the three dyes will alter the equilibrium of the neutral gray, resulting in a color tint. As a result, the neutral scale is not always without any chroma. Another limitation is that the reproducible gamut range is confined by the dye sets. Any color beyond the linear combination of the three primary dyes is not represented in the target's domain. In addition, uniformity, stability and non-fluorescence are factors to be considered.

In this thesis, Eastman Kodak Company Ektachrome Q-60E1 (IT8.7/1) and Fuji Photo Film Company Fujichrome IT8.7/1 were used as the transparent targets. Fujicolor

IT8.7/2 and Kodak Ektacolor Q-60C were used as the reflection targets. Independent test targets were created with a 6x6x6 digital factorial design sampling and 18 levels of neutral patches. These independent targets were generated with the same photographic materials as the standard IT8 type targets. Throughout this document, the numbering order for the colors on each target was from the top to the bottom starting from the left and lastly the gray patch starting from the left. The portrait image on the Kodak IT8 target was not used. Sample images of these targets are shown in Fig. 4.1-1

4.2 Metrology and Colorimetry

The committee for Graphic Arts Technologies Standards (CGATS) was accredited by the American National Standards Institute in 1989 to serve as the coordinator of graphic arts standards activities. As a result, the CGATS.5-1993 standard,⁷ "Graphic technology - Spectral measurement and colorimetric computation for graphic arts images" prepared by CGATS Working Group 4, was approved by the American National Standards Institute, Inc. on March 22, 1993 to specify a methodology for reflectance and transmittance spectral measurement and colorimetric parameter computation for graphic arts images. Consequently, the CGATS.5-1993 guidelines is followed throughout this thesis when possible.

(a)

(b)

(c)

(d)

FIG. 4.1-1. Sample images of the target materials: (a) Kodak IT8.7/1, (b) Fuji IT8.7/2, (c) Kodak Q-60C and (d) independent test target.

The CGATS.5-1993 standard is based on CIE illuminant D50 and the CIE 1931 standard observer as defined in CIE publication 15.2. The spectral data are collected between 360 nm and 780 nm in either 10 nm intervals and 20 nm intervals. The weighting values representing the product of illuminant and standard observer for 10 nm intervals accounting for bandpass as described by ASTM E-308, which is used in this thesis, are listed in Appendix A. It is noted that if the measured spectral data are at a wavelength greater than 360 nm, all the weighting values less than the first measured wavelength shall be summed and added to the weighting value for the first wavelength measured. If the measured spectral data are at a wavelength less than 780 nm, all the weighting values less than the first measured wavelength shall be summed and added to the weighting value for the last wavelength measured.

4.3 Spectral Measurement

4.3.1 Transparent Target

The spectral transmittance factor of each transparent sample was measured with a Photo Research Spectrascan PR-703A Spectraradiometer in DuPont Printing & Publishing, ADIP Group Color Laboratory. The PR-703A Spectraradiometer measures in the range of 390 nm to 730 nm with 2 nm increment and 5 nm bandwidth. A diffraction grating and multi-element photodetector comprise the system.³⁷ A tungsten halogen lamp with Corning filter (type #5900) was used as the light source in a 0/0 geometry.

Since the colorimetric computation is based on the ASTM weighting which is in 10 nm increments and for 10 nm bandpass and the spectral readings from the PR-703A are in 2 nm increment and with 5 nm bandpass, the spectral readings from the PR-703A were

averaged for every 5 readings of each exact 10 nm point (-2 nm, -4 nm, +0 nm, +2 nm and +4 nm) to convert the data from 2 nm increment in 5 nm bandwidth to 10 nm increment in 10 nm bandwidth before the colorimetric computation.³⁸

4.3.2 Reflection Target

The spectral reflectance factor of each reflection sample was measured with a GRETAG SPM 60 spectrophotometer. The Gretag SPM 60 provides spectral reflectance factor data as well as the standard tristimulus and CIELAB readings. Its spectral reading is in the range between 380 nm to 730 nm with 10 nm increment. The light source is a gas-filled tungsten light type A in a 45/0 geometry. A filter wheel can be used to convert the light source to D65 or to add a polarized filter or no filter at all. The D65 filter was used. The measurement aperture is fixed at 3.5 mm without any interchangeable aperture. A white reference plate is built-in on its housing stand for white calibration.³⁹

Each of the spectral data was an average of five measurements made without replacement. Each sample was backed by a black mat surface.

4.4 System Configuration

A Howtek Scanmaster D4000 drum scanner was used in this thesis. The D4000 scanner is based on the photomultiplier tube (PMT) technology. Three matched PMT sensors with dichroic beam splitters and interference filters were used for collecting signals. Two tungsten halogen reflector lamps were used as the light sources for the reflectance and the transmittance modes, respectively. A white strip is built-in longitudinally on the drum to provide the white reference for the opaque material and the dark reference for the transparent material. The effective mounting area on the drum is 11

inches by 10.2 inches. The drum speed is ranged between 300 to 1200 rpm. It supports automatic and manual focusing. Both SCSI and GPIB interfaces are included in the scanner.⁴⁰

The D4000 scanner is capable of reaching a spatial resolution ranging from 50 to 4000 dots per inch. The output signals can be either 8-bit or 12-bit data per channel in linear or logarithmic mode. A C language interface library is available from Howtek for third party's software development,⁴¹ with which a C program was written in Think C 6.0 platform to interface with the scanner for outputting raw red, green and blue signals. This program operated using a Macintosh Quadra 700 computer with a SCSI interface to the D4000 scanner.

5. Results and Discussion

5.1 Transparent Material - Kodak Ektachrome

A Kodak IT8.7/1 4x5 transmission target was used as the target object. The material base of this target is the Kodak Professional Ektachrome 100 Plus professional film. The spectral data of each color patch on the IT8.7/1 target was recorded in the order as described in the experimental design section. The spectral data were collected from 390 nm to 730 nm at 2 nm increment and converted into 10 nm increment. The measurement was performed at DuPont Printing & Publishing, ADIP Group Color Laboratory.

5.1.1 Material Analysis

The first step in the material analysis was to determine the base transmittance, $T_g(\lambda)$, for the spectral model in Eq. (9). According to the IT8.7/1 specification, the minimum density (D-min, the maximum transmittance that a photographic film can achieve) of the material is located at the lower-left corner on the target. A global search of all transmittances in every measured wavelength was performed and revealed that the maximum transmittance is always found in the designated D-min patch, except for very small difference in the lower wavelength region. The global maximum transmittance and the transmittance of the D-min patch are shown in Fig. 5.1-1. In this thesis, the global maximum transmittance of every wavelength was taken as the material's base transmittance, $T_g(\lambda)$. Data can be found in Appendix B.

FIG. 5.1-1. Global maximum transmittance (solid line) and transmittance of D-min patch (dashed line) are almost the same for Kodak IT8.7/1 target.

After removing the base transmittance by dividing $T_g(\lambda)$ from every i th patch's spectral data, $T_i(\lambda)$, and transforming it with a natural logarithm function, the overall absorptivity, $K_i(\lambda)$, of the three dyes for the i th color was obtained as follow:

$$K_i(\lambda) = -\ln(T_i(\lambda) / T_g(\lambda))$$

where $K_i(\lambda) = c_{ic} k_c(\lambda) + c_{im} k_m(\lambda) + c_{iy} k_y(\lambda)$. The c_{ic} , c_{im} and c_{iy} are the concentrations, and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are the unit spectral absorptivities of the cyan, magenta and yellow dyes, respectively.

With all $K_i(\lambda)$ of each color patch, the unit absorptivity for each dye was analyzed with the principal component analysis of the SYSTAT statistics software package.³⁰ A

covariance matrix with the "equamax" rotation was used to estimate the three eigenvectors. These eigenvectors were considered as the global eigenvectors since they represented the overall gamut variance among all the color patches. The first three eigenvectors each explained variances of 33.499%, 33.664%, and 32.795%, respectively. With a total of 99.958% explained by the first three eigenvectors, it indicated that these three eigenvectors described the film characteristics very well. The results of this analysis are summarized in Table II.

Three principal component analyses on the $K_i(\lambda)$ values of each cyan, magenta and yellow color ramp (with 12 patches in each ramp) were performed respectively with covariance matrix form without any rotation. These ramps are located on the 13th, 14th and 15th column of the IT8.7/1 4X5 target. The results of the analyses are also summarized in Table II. As expected, most of the variance in each analysis was explained by the first eigenvector, which implied the unit absorptivity of the cyan, magenta and yellow dye, respectively. It was also noticed that all the first eigenvectors from each of the cyan, magenta and yellow column did not totally explain the variance for each color, which suggests that these colors were not formed by a single dye. Since the first three eigenvectors accounted for 99.9% of the total variance, it confirms that three primaries are sufficient to represent the material's spectral characteristics.

TABLE II. Principal component analysis results: percentage of variance explained by the eigenvectors of Kodak IT8.7/1 target.

Sampling population (size)	Explained by 1st eigenvector	Explained by 2nd eigenvector	Explained by 3rd eigenvector	Total
All patches (264)	33.499%	33.664%	32.795%	99.958%
Cyan ramp (12)	99.702%	0.271%	0.024%	99.997%
Magenta ramp (12)	99.309%	0.678%	0.010%	99.997%
Yellow ramp (12)	99.821%	0.165%	0.010%	99.996%

Three linear regressions were further performed to rotate the three global eigenvectors to the vector spaces formed by the three color ramps. The three global eigenvectors were used as the independent variables and each ramp's first eigenvector was used as the dependent variable. There was no constant term in the regression since no offset was involved. All the terms were significant with the 2-tail P value less than 0.001. The regression results are summarized in Table III. Based on the estimated cyan, magenta and yellow eigenvectors from the regression, the unit absorptivities of the Kodak Professional Ektachrome 100 Plus film are revealed as shown in Fig. 5.1-2 and the actual numbers are listed in Appendix B for reference. Note that, these absorptivity units were based on the natural logarithm instead of the 10 based log.

TABLE III. Regression results: ramp eigenvectors against global eigenvectors for Kodak IT8.7/1 target.

Equation term	Coefficients for cyan ramp	Coefficients for magenta ramp	Coefficients for yellow ramp
global cyan	0.871	-0.190	-0.160
global magenta	-0.101	0.997	-0.314
global yellow	-0.089	-0.093	1.060
R square values	0.999	1.000	0.998

FIG. 5.1-2. (a) Global eigenvectors (solid line) and eigenvectors from cyan, magenta and yellow ramps (dashed line) of Kodak IT8.7/1 target. (b) Final rotated eigenvectors of Kodak IT8.7/1 target.

5.1.2 Prediction of Actual Concentrations

With the rotated eigenvectors, a C program was used to predict the concentrations of the three dyes to yield tristimulus matches for each color patch (without the base transmittance, T_g). The tristimulus matches were performed for illuminant D50. If the eigenvectors are faithful to the absorptive properties of the film and if the Beer-Bouguer theory holds, the tristimulus matches will agree with spectral matches. Spectral matches are plotted in Fig. 5.1-3 for patches 1, 9 and 18 of the neutral gray. Further verification was done by calculating color differences between the measured and the predicted spectra from a spectrally dissimilar light source, in this case illuminant A. Color differences for illuminant A were calculated as an index of metamerism; the average was 0.2 (maximum at 0.6) and the histogram is plotted in Fig. 5.1-4. The small color differences indicate that the model accurately describes the color formulation property of this material.

FIG. 5.1-3. Spectral transmittance factor of predicted (solid line) and measured (dashed line) grays resulting from the tristimulus matching algorithm for illuminant D50.

FIG. 5.1-4. Histogram of color differences for illuminant A between measured and predicted spectra by means of the tristimulus matching algorithm under illuminant D50 for Kodak IT8.7/1 target.

5.1.3 Image Scanning

A C program was written with the aid of Howtek's software interface kit to gather direct red, green and blue scanner readings. The scanning was done in linear mode and all the internal look-up tables were set as linear. Both 12-bit and 8-bit scans were performed. The scanning resolution was set at 500 dpi to keep the image file a manageable size.

In the image file, there were about 7,700 pixels per red, green and blue channel for each color patch and more for the bottom neutral patches. The exact digital counts were from the average of the center 2500 pixels of each color patch. The digital counts were normalized by 4095 for 12-bit data and by 255 for 8-bit data to confine the range between 0 and 1.

5.1.4 Building Characterization Model

The linearization process was performed to find a linear relationship between concentrations of the Kodak IT8.7/1 target's neutral patches against their corresponding 12-bit red, green, and blue digital counts (denoted d_r , d_g and d_b). Based on Eq. (29), it was expected that the natural logarithm of the normalized scanner digital counts should be approximately linear to the concentration. Fig. 5.1-5 (a) is an example plot to show the relationship between the scanner red digital counts (d_r) and the corresponding cyan concentrations (C_c) of the gray scale of the Kodak IT8.7/1 target. As shown in Fig. 5.1-5 (b), after the scanner red digital counts were normalized and then transformed with a natural logarithm function, the relationship become much more linear.

The complete scanner linearization was performed by regressing the concentrations of the neutral patches against their corresponding 12-bit red, green, and blue digital counts

through the transformation (by normalization and natural logarithm) with a fifth order polynomial equation. A forward stepwise model with a tolerance at 0.01 was used. The R square values were all at 1.0. The regression results were:

$$D_r = -0.27423 + 0.85435 R + 0.00004 R^5$$

$$D_g = -0.24095 + 0.63416 G + 0.00007 G^5$$

$$D_b = -0.21947 + 0.55854 B + 0.00005 B^5$$

$$\text{where } R = \ln(d_r / (2^{12} - 1)),$$

$$G = \ln(d_g / (2^{12} - 1)),$$

$$B = \ln(d_b / (2^{12} - 1)),$$

d_r , d_g and d_b are the red, green, and blue digital counts for 12-bit scan. The fact that the constant terms are significant might suggest the existence of the dark current for every channel. These regression formulae translate scanner red, green and blue digital counts of each patch to the transformed digital readings, D_r , D_g and D_b . An example of the linearization results is shown in Fig. 5.1-5 (c), where the transformed red digital counts (D_r) were plotted against their corresponding cyan concentrations.

Ideally, if the scanner's sensor spectral responsivities are narrow enough, the scanner's transformed digital readings would be linearly related to the material's concentrations. To verify this assumption, linear and non-linear stepwise regression models were used to relate the transformed digital readings to the concentrations.

FIG. 5.1-5. Example plots of cyan concentrations against (a) original (b) normalized and natural logarithm transformed (c) final linearized red scanner digital counts of Kodak IT8.7/1 target's neutral patches.

The linear model included a 3x3 matrix based on the first order terms. Stepwise regression was used to derive the model coefficients of the independent variables - transformed digital readings (D_r , D_g and D_b), for the predicted cyan, magenta and yellow concentrations. The regression results are summarized in Table IV. The concentration differences between model predictions and actual concentrations are plotted against actual concentrations as shown in Fig. 5.1-6. There is a trend in having higher prediction error when the concentration increases as shown in Fig 5.1-6 (b) and (c). This implies that this 3 by 3 linear model is not sufficient to represent the material property in higher concentration. This may be caused by the interaction between the dyes, stronger scattering effect when the concentration is higher or the wide-band nature of the scanner responsivities.

TABLE IV. Regression results of the 3 by 3 model (12-bit scan) for the Kodak IT8.7/1 target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
D_r	1.421	-0.179	-0.036
D_g	-0.540	1.396	-0.302
D_b	0.040	-0.196	1.405
R square value	0.999	1.000	1.000
S. S. Residual	0.512	0.209	0.190

FIG. 5.1-6. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 3 model (12-bit scan) for Kodak IT8.7/1 target.

The predicted concentrations for all color patches were used to reconstruct the spectral transmittances with the prior derived eigenvectors and the base transmittance. The reconstructed spectral transmittance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and the 2 degree observer. The average ΔE^*_{ab} color difference between the measured data and from the 3 by 3 model's prediction is 0.98, with maximum at 7.04 and standard deviation of 0.60. The histogram of the ΔE^*_{ab} error is plotted in Fig. 5.1-7. The performance of the 3 by 3 model is analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.1-8. An important quality factor of the model performance is the ability to maintain the gray balance in the neutral tones. By definition, the neutral tones are the colors of zero chroma. The ability of this model to keep the gray balance can be observed in Fig. 5.1-8 (b), where the ΔE^*_{ab} errors around zero chroma are in general smaller than the color errors in the higher chroma region.

FIG. 5.1-7. Histogram of color differences between measured and predicted spectra by means of the 3 by 3 model for 12-bit scan under illuminate D50 for Kodak IT8.7/1 target.

FIG. 5.1-8. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 3 model predictions (12-bit scan) for Kodak IT8.7/1 target.

The non-linear model included a 3 by 11 matrix based on the second order polynomial plus a $D_r * D_g * D_b$ cross term. Stepwise regression with forward selection (tolerance at 0.01) was used to derive the model coefficients of the independent variables: transformed digital readings (D_r , D_g and D_b), for the predicted cyan, magenta and yellow concentrations. The regression results are summarized in Table V. The concentration differences between model predictions and actual concentrations are plotted against actual concentrations as shown in Fig. 5.1-9. There are slight curvatures in Fig. 5.1-9 (b) and (c), which implies the model did not completely account for the material property. However compared with the results from the 3 by 3 model, this 3 by 11 non-linear model did improve the prediction accuracy and reduce the trend in having higher prediction error with higher concentration. It seems that the higher order terms are necessary in modeling this material and a more complicated model is needed to completely represent this material property.

TABLE V. Regression results of the 3 by 11 model (12-bit scan) for Kodak IT8.7/1 target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
Constant	-0.027	-0.012	-0.024
D_r	1.427	-0.196	-0.045
D_g	-0.565	1.472	-0.310
D_b	0.068	-0.190	1.490
$D_r * D_g$	-0.085	0.020	Not significant
$D_r * D_b$	Not significant	-0.005	0.011
$D_g * D_b$	Not significant	-0.025	0.006
$D_r * D_g * D_b$	Not significant	0.003	Not significant
D_r^2	0.037	-0.006	-0.002
D_g^2	0.051	-0.025	Not significant
D_b^2	-0.008	0.009	-0.038
R square value	1.000	1.000	1.000
S. S. Residual	0.053	0.032	0.033

FIG. 5.1-9. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 11 model (12-bit scan) for Kodak IT8.7/1 target.

The predicted concentrations from the 3 by 11 model were used to reconstruct the spectral transmittances of all color patches with the prior derived eigenvectors and the base transmittance. The reconstructed spectral transmittance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and the 2 degree observer. The average ΔE^*_{ab} color differences between measured data and the 3 by 11 model's prediction is 0.37, with maximum at 1.03 and the standard deviation of 0.18. The histogram of the ΔE^*_{ab} error is plotted in Fig. 5.1-10. The performance of the 3 by 11 model is further analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.1-11. As shown in Fig. 5.1-11 (b), the color differences at the zero chroma area are distributed under $0.5 \Delta E^*_{ab}$ range, which indicates that this 3 by 11 model keeps a good gray balance for the neutral tones.

FIG. 5.1-10. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for 12-bit scan under illuminant D50 for Kodak IT8.7/1 target.

FIG. 5.1-11. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (12-bit scan) for Kodak IT8.7/1 target.

A comparison between Fig. 5.1-7 and Fig. 5.1-10 may reveal that the distributions of the model error of the 3 by 3 and the 3 by 11 models are not in the same range. Further F tests were performed to test the hypothesis that the average color differences of these two models are the same. The critical value of the F distribution for 264 samples with α error at 0.05 is smaller than 1.35.⁴² The F value is 11.11 (from $(0.60 / 0.18)^2$), which is greater than the critical value. Therefore, the hypothesis is rejected. In other words, the two models have statistically different performances.

For the 3 by 3 model, as shown in Fig. 5.1-8, the color difference increases as the chroma increases. The maximum error at 7.04 is from the last patch on the red color ramp, which has the highest concentrations of magenta and yellow. The other data points with high color difference are also with high concentrations. Similar trends can be observed in Fig. 5.1-6 that the prediction error increases as the concentration increases. It is clear that the 3 by 3 linear model does not perform well in the high concentration region.

On the other hand, as shown in Fig. 5.1-9, the 3 by 11 model introduces less predicted concentration error than the 3 by 3 model did. It is also noted that the sum of square residual error for the 3 by 11 model in Table V is 10% of that for the 3 by 3 model in Table IV. The small prediction error would translate into a small color difference error as shown in Fig. 5.1-11, also showing a better normality in the high chroma region than for the 3 by 3 model. The non-linear nature of the 3 by 11 model does improve the performance. It is suspected that the scanner channel responsivities are so wide that non-linear functions are needed to model the relationship between the integral and analytic densities.

A further study was performed to answer the question of how much more model error is introduced by the quantization difference between the 12-bit and the 8-bit scan modes. Another characterization model (linearization and then 3 by 11 model) was built for the 8-bit d_r , d_g and d_b digital counts to generate predicted concentrations. The model coefficients of the 3 by 11 model are listed in Table VI. The concentration differences between model predictions and actual concentrations are plotted against actual concentrations as shown in Fig. 5.1-12. It is noticed that the model errors in Fig. 5.1-12 show a curvature trend, which implies that the model does not completely explain the material property. It is suspected that the scattering between dyes are involved. However compared with the model errors in Fig. 5.1-9, the 3 by 11 non-linear model could not explain the 8-bit data that well, especially in the higher concentration area.

The average ΔE^*_{ab} color differences between the measured data and the 8-bit 3 by 11 model's prediction is 0.66, with a maximum of 1.91 and the standard deviation of 0.33. The performance of the 8-bit 3 by 11 model is analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.1-13. As shown in Fig. 5.1-13 (b), the ΔE^*_{ab} errors around zero chroma are in general very small, which indicates that this model maintains a good gray balance. The histogram of the ΔE^*_{ab} error is shown in Fig. 5.1-14.

TABLE VI. Regression results of the 3 by 11 model (8-bit scan) for Kodak IT8.7/1 target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
Constant	Not significant	Not significant	Not significant
D_r	1.361	-0.172	-0.057
D_g	-0.511	1.380	-0.284
D_b	0.039	-0.164	1.398
$D_r * D_g$	-0.089	0.017	Not significant
$D_r * D_b$	Not significant	-0.007	0.023
$D_g * D_b$	Not significant	-0.021	Not significant
$D_r * D_g * D_b$	Not significant	Not significant	-0.004
D_r^2	0.056	-0.010	Not significant
D_g^2	0.037	0.009	-0.005
D_b^2	Not significant	Not significant	Not significant
R square value	1.000	1.000	1.000
S. S. Residual	0.154	0.118	0.130

FIG. 5.1-12. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 11 model (8-bit scan) for Kodak IT8.7/1 target.

FIG. 5.1-13. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (8-bit scan) for Kodak IT8.7/1 target.

FIG. 5.1-14. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for 8-bit scan under illuminant D50 for Kodak IT8.7/1 target.

The 3 by 11 model for the 8-bit data does not induce a higher model error in the high chroma region as shown in Fig. 5.1-13; however, it shows a trend in having a higher model error as the lightness increases. The concentration differences between actual concentrations and model predictions also increase in the high concentration area as shown in Fig. 5.1-12. The sum of square errors in Table VI for the 3 by 11 model in 8-bit scan are smaller than those in Table IV for the 3 by 3 model in 12-bit scan.

In regarding the mean color difference, the results of the pair-wise F tests reveal that the 12-bit 3 by 11 model is better than the 8-bit 3 by 11 model (F value 3.38) and the 8-bit 3 by 11 model is better than the 12-bit 3 by 3 model (F value 3.31). The performance of these models is summarized in Table VII. It is concluded that the 3 by 11 model in 12-bit mode has the best model performance. The non-linear model with 8-bit scan performs better than the linear model with 12-bit scan, i.e., the non-linear model is more critical than the 12-bit signal resolution. Furthermore, for the 8-bit mode, the fact that all color

differences are under ΔE^*_{ab} 2.0 with an average ΔE^*_{ab} of 0.66 indicates a fairly good model performance. Considering the fact that each 12-bit pixel takes two bytes memory space and the 8-bit pixel only takes half of the memory space, the 8-bit model could be useful for large size images.

Separate analysis was performed on these 3 models to compare the model performance in maintaining gray balance. Vector plots were generated using the measured L^* and C^*_{ab} values as the starting points and the predicted L^* and C^*_{ab} values as the ending points for the neutral patches as shown in Figs. 5.1-15 (a), (c) and (e). The ΔC^*_{ab} values were plotted against L^* values as shown in Figs. 5.1-15 (b), (d) and (f). The arrow direction indicates the model's trend. The length of the vector on the Y-axis indicates the chroma shift from the measured data to the predicted data. Comparing the vectors among Figs. 5.1-15 (a)-(f), one can conclude that the 3 by 11 model with 12-bit data had the least chroma shift for the neutral tones (no larger than $0.5 \Delta C^*_{ab}$), and the 3 by 11 model with 8-bit data had the largest chroma shift (larger than $1.5 \Delta C^*_{ab}$). The average ΔE^*_{ab} , ΔL^* , ΔC^*_{ab} , ΔH^*_{ab} between the measured and predicted data of the neutral patches were also calculated and summarized in Table VII. Note that the 3 by 3 model had the largest average hue shift. Vector plots on a^* and b^* coordinates were also generated for every other color of the cyan, magenta, yellow, red, green and blue ramps to show the hue shift from the measured data to the predicted data in Figs. 5.1-16 (a), (c) and (e). Corresponding vector plots on Δa^* and Δb^* coordinates were generated to show the hue shift from the measured data to the predicted data in Figs. 5.1-16 (b), (d) and (f). Note that all the hue shifts were very small according to the lengths of the vectors in Fig. 5.1-16.

TABLE VII. Performance summary for 3 different characterization methods for Kodak IT8.7/1 target.

Scanning mode	12 bit	12 bit	8 bit
Characterization method	Linearization plus 3 by 3 model	Linearization plus 3 by 11 model	Linearization plus 3 by 11 model
Overall avg. ΔE^*_{ab}	0.98	0.37	0.66
Standard deviation	0.60	0.18	0.33
Maximum ΔE^*_{ab}	7.04	1.03	1.91
Avg. gray ΔE^*_{ab}	0.72	0.35	0.55
Avg. gray ΔL^*_{ab}	0.17	0.21	0.25
Avg. gray ΔC^*_{ab}	0.27	0.21	0.37
Avg. gray ΔH^*_{ab}	0.60	0.10	0.22
Performance rating	3	1	2

FIG. 5.1-15. Vector plots of the chroma shift between the L^* and C^*_{ab} as well as ΔC^*_{ab} values from measured and model predictions from (a, b) 3 by 3 model (12-bit scan), (c, d) 3 by 11 model (12-bit scan) (e, f) 3 by 11 model (8-bit scan) of the Kodak IT8.7/1 target's neutral tones.

(a)

(b)

(c)

(d)

(e)

(f)

FIG. 5.1-16. Vector plots of $[a^*, b^*]$ and $[\Delta a^*, \Delta b^*]$ values of the measured and predicted data from (a, b) 3 by 3 model (12-bit scan), (c, d) 3 by 11 model (12-bit scan) (e, f) 3 by 11 model (8-bit scan) of the Kodak IT8.7/1 target's c, m, y, r, g, and b ramps.

5.1.5 Performance Verification

An independent Ektachrome 4X5 film was exposed with a CRT-based film recorder using a digital image with a 6x6x6 digital factorial design sampling and 18 levels of neutral patches. The film was processed at the R.I.T. photo processing laboratory with regular E-6 processing. This film was spectrally measured and then independently scanned in 12-bit mode with the same procedure as for the Kodak IT8.7/1 target.

The 12-bit scanner digital readings for each color patch were processed through the linearization equations and then the 3x11 model to get the predicted concentrations since the 12-bit 3 by 11 model had the best performance. The concentrations were then used to calculate the spectral property of each color patch with the prior derived eigenvectors as well as with the film base transmittance. The resulting spectral transmittance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and the 2 degree observer. The average color difference between the measured data and the model predictions was $0.71 \Delta E^*_{ab}$ unit, with the standard deviation of 0.36. The maximum color difference was at 1.78. The ΔE^*_{ab} differences are plotted against L^* , C^*_{ab} and h_{ab} respectively in Fig. 5.1-17 to show the normality of the model error. These results indicate that the linearization process with the 3 by 11 nonlinear model worked well. Given the possible variance introduced from different batches of film or different lines of film processing or even the repeatability of the spectrophotometer, this result is considered quite good. The histogram of the color difference resulting from the scanner calibration model is shown in Fig. 5.1-18.

FIG. 5.1-17. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (12-bit scan) for an independent Kodak Ektachrome target.

FIG. 5.1-18. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for an independent Kodak Ektachrome target (12-bit scan).

5.2 Transparent Material - Fuji Fujichrome

A Fuji IT8.7/1 4x5 transmission target was used as the target object. The material base of this target is the Fujichrome 100 Professional D film. The spectral data of each color patch on the Fuji IT8.7/1 target were measured in the same method as described in section 5.1. The data were recorded in the order as described in the experimental design section. The spectral data of all 288 patches were used for the model derivation since the skin tones are represented by three ramps of skin colors and there is no facial image on the Fuji target. The spectral data were collected from 390 nm to 730 nm at 2 nm increment and converted into 10 nm increment. The measurement was also performed at DuPont Printing & Publishing, ADIP Group Color Laboratory.

5.2.1 Material Analysis

The first step in the material analysis was to determine the base transmittance, $T_g(\lambda)$, of the spectral model in Eq. (9). According to the IT8.7/1 specification, the minimum density (D-min, the maximum transmittance that a photographic film can achieve) of the material is located at the lower-left corner on the target. A global search of all transmittances in every measured wavelength was performed and revealed that the maximum transmittance is mostly found in the designated D-min patch, except for some differences in the higher wavelength region. The global maximum transmittance and the transmittance of the D-min patch are shown in Fig. 5.2-1. The global maximum transmittance of every wavelength was taken as the material's base transmittance, $T_g(\lambda)$. These data can be found in Appendix B.

FIG. 5.2-1. Global maximum transmittance (solid line) and transmittance of D-min patch (dashed line) for Fuji IT8.7/1 target.

After removing the base transmittance by dividing $T_g(\lambda)$ from every i th patch's spectral data, $T_i(\lambda)$, and transforming it with a natural logarithm function, the overall absorptivity, $K_i(\lambda)$, of the three dyes for the i th color was obtained as follow:

$$K_i(\lambda) = -\ln(T_i(\lambda) / T_g(\lambda))$$

where $K_i(\lambda) = c_{ic} k_c(\lambda) + c_{im} k_m(\lambda) + c_{iy} k_y(\lambda)$. The c_{ic} , c_{im} and c_{iy} are the concentrations, and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are the unit spectral absorptivities of the cyan, magenta and yellow dyes, respectively.

With all $K_i(\lambda)$ of each color patch, the unit absorptivity for each dye was analyzed with the principal component analysis of the SYSTAT statistics software package.³⁰ A

covariance matrix with the "equamax" rotation was used to estimate the three eigenvectors. These eigenvectors were considered as the global eigenvectors since they represented the overall gamut variance among all the color patches. The first three eigenvectors each explained variances of 39.616%, 29.627%, and 30.728%, respectively. With a total of 99.971% explained by the first three eigenvectors, it indicated that these three primary absorptivities described the film characteristics very well. The results of this analysis is summarized in Table VIII.

Another three principal component analyses on the $K_i(\lambda)$ values of each cyan, magenta and yellow color ramp (with 12 patches in each ramp) were performed respectively with covariance matrix form without any rotation. These ramps are located on the 13th, 14th and 15th columns of the IT8.7/1 4X5 target. The results of the analyses are also summarized in Table VIII. As expected, most of the variance in each analysis was explained by the first eigenvector, which implied the unit absorptivity of the cyan, magenta and yellow dye, respectively.

TABLE VIII. Principal component analysis results: percentage of variance explained by the eigenvectors of Fuji IT8.7/1 target.

Sampling population (size)	Explained by 1st eigenvector	Explained by 2nd eigenvector	Explained by 3rd eigenvector	Total
All patches (288)	39.616%	29.627%	30.728%	99.971%
Cyan ramp (12)	99.938%	0.054%	0.006%	99.998%
Magenta ramp (12)	99.933%	0.058%	0.006%	99.996%
Yellow ramp (12)	99.861%	0.112%	0.022%	99.994%

Three linear regressions were further performed to rotate the three global eigenvectors to the vector spaces formed by the three color ramps. The three global eigenvectors were used as the independent variables and each ramp's first eigenvector was used as the dependent variable. There was no constant term in the regression since no offset was involved. All terms were significant with the 2-tail P value less than 0.001. The regression results are summarized in Table IX. Based on the estimated cyan, magenta and yellow eigenvectors from the regression, the unit absorptivities of the Fujichrome 100 Professional D film are revealed as shown in Fig. 5.2-2 and the actual numbers are listed in Appendix B for reference. Note that, these absorptivity units were based on the natural logarithm instead of the traditional 10 based log.

TABLE IX. Regression results: ramp eigenvectors against global eigenvectors for Fuji IT8.7/1 target.

Equation term	Coefficients for cyan ramp	Coefficients for magenta ramp	Coefficients for yellow ramp
global cyan	1.054	-0.247	-0.232
global magenta	-0.012	1.195	-0.337
global yellow	-0.188	-0.132	1.195
R square values	1.000	1.000	0.999

FIG. 5.2-2. (a) Global eigenvectors (solid line) and eigenvectors from cyan, magenta and yellow ramps (dashed line) of Fuji IT8.7/1 target. (b) Final rotated eigenvectors of Fuji IT8.7/1 target.

5.2.2 Prediction of Actual Concentrations

With the rotated eigenvectors, a C program was used to predict the concentrations of the three dyes to yield tristimulus matches for each color patch (without the base transmittance, T_g). The tristimulus matches were performed for illuminant D50 first. If the eigenvectors are faithful to the absorptive properties of the film and if the Beer-Bouguer law holds, the tristimulus matches will agree with spectral matches. It was verified by calculating color differences between the measured and the predicted spectra from a spectrally dissimilar light source, in this case illuminant A. Color differences for illuminant A were calculated as an index of metamerism; the average was 0.1 (maximum at 0.4) and the histogram is plotted in Fig. 5.2-3. The small color differences indicate that the model accurately describes the color formulation property of Fujichrome.

FIG. 5.2-3. Histogram of color differences for illuminant A between measured and predicted spectra by means of the tristimulus matching algorithm under illuminant D50 for Fuji IT8.7/1 target.

5.2.3 Image Scanning

A C program was written with the aid of Howtek's software interface kit to gather direct red, green and blue scanner readings. The scanning was done in 12-bit linear mode and all the internal look-up tables were set as linear. The scanning resolution was set at 500 dpi.

In the image file, there were about 7,700 pixels per red, green and blue channel for each color patch and more for the bottom neutral patches. The exact digital counts were from the average of the center 2500 pixels of each color patch. The digital counts were normalized by 4095 to confine the range between 0 and 1.

5.2.4 Building Characterization Model

The linearization process was performed to find a linear relationship between concentrations of the Fuji IT8.7/1 target's neutral patches against their corresponding 12-bit r, g, and b digital counts (denoted d_r , d_g and d_b). Based on Eq. (29), it was expected that the natural logarithm of the normalized scanner digital counts should be approximately linear to the concentration. Fig. 5.2-4 (a) is an example plot to show the relationship between the scanner red digital counts (d_r) and the corresponding cyan concentrations (C_C). As shown in Fig. 5.2-4 (b), after the scanner red digital counts were normalized and then transformed with a natural logarithm function, the relationship become much linear.

The complete scanner linearization was performed by regressing the concentrations of the neutral patches against their corresponding 12-bit red, green, and blue digital counts with a fifth order polynomial equation. A forward stepwise model with a tolerance at 0.01 was used. The R square values were all at 1.0. The regression results were:

$$D_r = -0.24607 + 0.68071 R + 0.00004 R^5$$

$$D_g = -0.21636 + 0.52220 G + 0.00024 G^4$$

$$D_b = -0.25517 + 0.53836 B + 0.00004 B^5$$

$$\text{where } R = \ln(d_r / (2^{12} - 1)),$$

$$G = \ln(d_g / (2^{12} - 1)),$$

$$B = \ln(d_b / (2^{12} - 1)),$$

d_r , d_g and d_b are the red, green, and blue digital counts for 12-bit scan. The fact that the constant terms are significant might suggest the existence of the dark current for every channel. These regression formulae translate scanner red, green and blue digital counts of each patch to the transformed digital readings, D_r , D_g and D_b . An example of the linearization results is shown in Fig. 5.2-4 (c), where the transformed red digital counts (D_r) were plotted against their corresponding cyan concentrations.

Prior experiments on Ektachrome indicated that the non-linear 3 by 11 model performed better than the 3 by 3 linear model. A 3 by 11 matrix based on the second order polynomial plus a $D_r \cdot D_g \cdot D_b$ cross term was used as the characterization model. Stepwise regression with forward selection (tolerance at 0.01) was used to derive the model coefficients of the independent variables (transformed digital readings, D_r , D_g and D_b) with the dependent variables (the predicted cyan, magenta and yellow concentrations). The regression results are summarized in Table X. The concentration differences between the model predictions and the actual concentrations are plotted against actual concentrations as shown in Fig. 5.2-5. From the distribution of the concentration difference shown in Fig. 5.2-5, it is noted that this 3 by 11 nonlinear model performed fairly well, except for a few data of high yellow concentration. The sum of square errors in Table X also indicate that there was higher residual error for the yellow dye compared with cyan and magenta dyes.

FIG. 5.2-4. Example plots of cyan concentrations against (a) original (b) normalized and natural logarithm transformed (c) final linearized red scanner digital counts of Fuji IT8.7/1 target's neutral patches.

The predicted concentrations from the 3 by 11 model were used to reconstruct the spectral transmittances of all the color patches with the prior derived eigenvectors and the base transmittance. The reconstructed spectral transmittance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and 2 degree observer. The average ΔE^*_{ab} color differences between the measured data and the 3 by 11 model's prediction is 0.41, with a maximum of 1.57 and the standard deviation of 0.21. The performance of the 3 by 11 model is further analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.2-6. The small ΔE^*_{ab} error in the zero chroma area in Fig. 5.2-6 (b) indicates that this model preserves the gray balance very well. The histogram of the ΔE^*_{ab} error is plotted in Fig. 5.2-7.

TABLE X. Regression results of the 3 by 11 model (12-bit scan) for Fuji IT8.7/1 target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
Constant	-0.021	-0.001	-0.015
D_r	1.263	-0.180	Not significant
D_g	-0.360	1.386	-0.366
D_b	0.057	-0.140	1.427
$D_r * D_g$	-0.087	0.023	-0.009
$D_r * D_b$	0.016	-0.010	Not significant
$D_g * D_b$	Not significant	-0.024	Not significant
$D_r * D_g * D_b$	-0.003	0.004	0.006
D_r^2	0.030	-0.005	Not significant
D_g^2	0.041	-0.006	Not significant
D_b^2	-0.006	0.009	-0.036
R square value	1.000	1.000	1.000
S. S. Residual	0.027	0.015	0.045

FIG. 5.2-5. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 11 model (12-bit scan) for Fuji IT8.7/1 target.

FIG. 5.2-6. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (12-bit scan) for Fuji IT8.7/1 target.

FIG. 5.2-7. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for 12-bit scan under illuminant D50 for Fuji IT8.7/1 target.

The largest ΔE^*_{ab} error (1.57) corresponds to the darkest yellow of the yellow ramp. The second darkest yellow also has a higher ΔE^*_{ab} of 1.0. It seems that the model does not perform that well for the yellow dye in high concentration, which agrees with the finding from the residual error in the regression analysis. However, considering the fact that most of the ΔE^*_{ab} errors are located between 0.2 and 0.6 as shown in Fig. 5.2-7, the overall model performance is quite good.

Separate analysis was performed to verify the model performance on maintaining gray balance. Vector plots were generated using the measured L^* and C^*_{ab} values as the starting points and the predicted L^* and C^*_{ab} values as the ending points for the neutral

patches as shown in Fig. 5.2-8 (a). The ΔC^*_{ab} values were also plotted against L^* values as shown in Fig. 5.2-8 (b). The arrow direction indicates the model's trend. The length of the vector on the Y-axis indicates the chroma shift from the measured data to the predicted data. As shown in Figs. 5.2-8 (a) and (b), the chroma shifts of these neutral patches by the model predictions are quite small (no larger than $1.0 \Delta C^*_{ab}$). The average ΔE^*_{ab} , ΔL^* , ΔC^*_{ab} , ΔH^*_{ab} between the measured and predicted data of the neutral patches were 0.38, 0.09, 0.29 and 0.15, respectively. This 3 by 11 non-linear model preserves good gray balance. Vector plots on a^* and b^* coordinates as well as Δa^* and Δb^* coordinates were generated for every other color of the cyan, magenta, yellow, red, green and blue ramps to show the hue shift from the measured data to the predicted data in Fig. 5.2-9 (a) and (b). Note that all the hue shifts are very small according to the lengths of the vectors in Figs. 5.2-9 (a) and (b).

(a)

(b)

FIG. 5.2-8. Vector plots of the chroma shift between the L^* and (a) C^*_{ab} and (b) ΔC^*_{ab} from measured and model predictions of the Fuji IT8.7/1 target's neutral tones.

(a)

(b)

FIG. 5.2-9. Vector plots: (a) between a^* and b^* , (b) between Δa^* and Δb^* of the measured and predicted data of the Fuji IT8.7/1 target's c, m, y, r, g, and b ramps.

5.2.5 Performance Verification

An independent Fujichrome 4X5 film was exposed with a CRT-based film recorder using a digital image with a 6x6x6 factorial design sampling and 18 levels of neutral patches. The film was processed at the R.I.T. photo processing lab with regular E-6 processing. This film was spectrally measured and then independently scanned in 12-bit mode with the same procedure as for the Fuji IT8.7/1 target.

The 12-bit scanner digital readings for each color patch were processed through the linearization equations and then the 3x11 model to get the predicted concentrations. The concentrations were then used to calculate the spectral property of each color patch with the prior derived eigenvectors as well as with the film base transmittance. The resulting spectral transmittance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and 2 degree observer. The average color differences between

the measured data and the model predictions was $0.67 \Delta E^*_{ab}$ unit, with standard deviation of 0.25. The maximum color difference was at 1.56. The histogram of the color difference resulting from the scanner calibration model is shown in Fig. 5.2-10. It is noticed that 95% of the model errors for this independent test target are under ΔE^*_{ab} of 0.8. The average color difference error from the independent test target is less than 2 times of the modeling target. The ΔE^*_{ab} differences are plotted against L^* , C^*_{ab} and h_{ab} respectively in Fig. 5.2-11 to show the normality of the model errors. The evenly distributed model errors in Fig. 5.2-11 indicate a good model performance. The scanner characterization model worked very well given the possible variance introduced from different batch of film or different line of film processing or even the repeatability of the spectrophotometer.

FIG. 5.2-10. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for an independent Fujichrome target (12-bit scan)

FIG. 5.2-11. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (12-bit scan) for independent Fujichrome target.

5.3 Opaque Material - Kodak Ektacolor Plus Paper

A Kodak Q-60C 5x7 paper target was used as the target object for opaque material since the Kodak IT8.7/2 target was not accessible at the time of this thesis. The material base of the Q-60C target is the Kodak Ektacolor Plus paper. Even though this Q-60C target is discontinued, a lot of design consideration for the IT8 target was originated from the Kodak Q-60C target. A noticeable difference is the designated D-min and D-max patches on the IT8 target were not in the Q-60C target.

There are 236 color patches on the Q-60C target. The spectral data of each color patch were measured and recorded in the order as described in the experimental design section. The spectral data of all the 236 patches were used for the model derivation. The spectral data were collected from 390 nm to 730 nm at 10 nm increment. The measurement was performed at the Munsell Color Science Laboratory.

5.3.1 Material Analysis

The first step in the material analysis was to determine the base reflectance, $R_g(\lambda)$, of the spectral model in Eq. (18). Since there is no designated minimum density patch (D-min, the maximum reflectance that a photographic paper can achieve) on the Q-60C target, a global search of all reflectances in every measured wavelength was performed and used as the maximum reflectance. The global maximum reflectance and the reflectance of the white patch on the bottom neutral strip are compared in Fig. 5.3-1. The global maximum reflectance of every wavelength was taken as the material's base reflectance, $R_g(\lambda)$. Data can be found in Appendix B.

FIG. 5.3-1. Global maximum reflectance (solid line) and reflectance of the white patch (dashed line) for Kodak Q-60C target.

After removing the base reflectance by dividing $R_g(\lambda)$ from every i th patch's spectral data, $R_i(\lambda)$, and transforming it with a natural logarithm function, the overall absorptivity, $K_i(\lambda)$, of the three dyes for the i th color was obtained as follow:

$$K_i(\lambda) = \ln(R_i(\lambda) / R_g(\lambda)) / -2.0$$

where $K_i(\lambda) = c_{ic} k_c(\lambda) + c_{im} k_m(\lambda) + c_{iy} k_y(\lambda)$. The c_{ic} , c_{im} and c_{iy} are the concentrations, and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are the unit spectral absorptivities of the cyan, magenta, and yellow dyes, respectively.

With all $K_i(\lambda)$ of each color patch, the unit absorptivity for each dye was analyzed with the principal component analysis of the SYSTAT statistics software package.³⁰ A

covariance matrix with the "equamax" rotation was used to estimate the three eigenvectors. These eigenvectors were considered as the global eigenvectors since they represented the overall gamut variance among all the color patches. Each of the first three eigenvectors explained variances of 46.405%, 24.916%, and 28.616%, respectively. Even though the overall variance explained is not as high as for the transmittance material, the 99.938 percentiles are still quite good. The results of this analysis are summarized in Table XI.

Three principal component analyses on the $K_i(\lambda)$ values of each cyan, magenta and yellow color ramp (with 12 patches in each ramp) were performed respectively with covariance matrix form without any rotation. These ramps are located on the 12th, 13th and 14th columns of the Q-60C paper target. The results of the analyses are also summarized in Table XI. As expected, most of the variance in each analysis was explained by the first eigenvector, which implied the unit absorptivity of the cyan, magenta and yellow dye, respectively.

TABLE XI. Principal component analysis results: percentage of variance explained by the eigenvectors of Kodak Q-60C target.

Sampling population (size)	Explained by 1st eigenvector	Explained by 2nd eigenvector	Explained by 3rd eigenvector	Total
All patches (236)	46.405%	24.916%	28.616%	99.938%
Cyan ramp (12)	99.944%	0.030%	0.016%	99.990%
Magenta ramp (12)	99.941%	0.036%	0.020%	99.997%
Yellow ramp (12)	99.844%	0.137%	0.013%	99.995%

Three linear regressions were further performed to rotate the three global eigenvectors to the vector spaces formed by the three color ramps. The three global eigenvectors were used as the independent variable and each of the first ramp eigenvector was used as the dependent variable respectively. There was no constant term in the regression since no offset was involved. All the terms were significant with the 2-tail P value less than 0.01. The regression results are summarized in Table XII. Based on the estimated cyan, magenta and yellow eigenvectors from the regression, the unit absorptivities of the Kodak Ektacolor Plus paper are revealed as shown in Fig. 5.3-2 and the actual numbers are listed in Appendix B for reference. Note that the rotation did reduce the unwanted absorption, especially for the yellow dye as shown in Fig. 5.3-2 (a). However, there is more secondary absorption for the cyan dye in the lower wavelength region than the transparent materials. Note that these absorptivity units were based on the natural logarithm instead of the traditional 10 based log.

TABLE XII. Regression results: ramp eigenvectors against global eigenvectors for Kodak Q-60C target.

Equation term	Coefficients for cyan ramp	Coefficients for magenta ramp	Coefficients for yellow ramp
global cyan	1.288	-0.302	-0.310
global magenta	0.171	1.537	-0.129
global yellow	0.054	-0.020	1.39
R square values	0.999	1.000	1.000

FIG. 5.3-2. (a) Global eigenvectors (solid line) and eigenvectors from cyan, magenta and yellow ramps (dashed line) of Kodak Q-60C target. (b) Final rotated eigenvectors of Kodak Q-60C target.

5.3.2 Prediction of Actual Concentrations

A C program was used to predict the concentrations of the three dyes to yield tristimulus matches for each color patch (excluding the base reflectance, R_g) with the rotated eigenvectors. The tristimulus matches were performed for illuminant D50 first. If the eigenvectors are faithful to the absorptive properties of the film and if the Kubelka-Munk theory holds, the tristimulus matches will agree with spectral matches. Spectral matches are plotted in Fig. 5.3-3 for patches 1, 9 and 18 of the neutral gray. Further verification was done by calculating color differences between the measured and the predicted spectra from a spectrally dissimilar light source, in this case illuminant A. Color differences for illuminant A were calculated as an index of metamerism; the average ΔE^*_{ab} was 0.2 (a maximum of 0.9) and the histogram is plotted in Fig. 5.3-4. These color differences are not as small as found in the transmittance material; however, the average is less than ΔE^*_{ab} of 0.2 and 92% of the color errors are under ΔE^*_{ab} of 0.5.

FIG. 5.3-3. Spectral reflectances of predicted (solid line) and measured (dashed line) grays resulting from the tristimulus matching algorithm for Q-60C target under illuminant D50.

FIG. 5.3-4. Histogram of color differences for illuminant A between measured and predicted spectra by means of the tristimulus matching algorithm under illuminant D50 for Kodak Q-60C target.

5.3.3 Image Scanning

A C program was implemented to gather direct red, green and blue scanner readings for the opaque materials. However, a problem was encountered in the scanner system when operating in 12-bit mode for the reflection target. This problem introduced strange offset values in the scanner digital readings as documented in Appendix F. Such problem was not found in the 8-bit mode for the reflection target. As a result, the scanning was performed in the 8-bit linear mode. All the internal look-up tables were set as linear. The scanning resolution was set at 500 dpi.

In the image file, there were about 20,000 8-bit pixels per red, green and blue channel for each color patch and more for the bottom neutral patches. The exact digital counts were from the average of the center 3600 pixels of each color patch. The digital counts were normalized by 255 to confine the range among 0 and 1.

5.3.4 Building Characterization Model

The linearization process was performed to find a linear relationship between concentrations of the Kodak Q-60C target's neutral patches against their corresponding 8-bit red, green, and blue digital counts (denoted d_r , d_g and d_b). Based on Eq. (29), it was expected that the natural logarithm of the normalized scanner digital counts should be approximately linear to the concentration. Fig. 5.3-5 (a) is an example plot to show the relationship between the scanner red digital counts (d_r) and the corresponding cyan concentrations (C_c) of the Kodak Q-60C target. As shown in Fig. 5.3-5 (b), after the scanner red digital counts were normalized and then transformed with a natural logarithm function, the relationship becomes more linear.

The complete scanner linearization was performed by regressing the concentrations of the neutral patches against their corresponding 8-bit red, green, and blue digital counts through the transformation (by normalization and natural logarithm) with a fifth order polynomial equation. A forward stepwise model with a tolerance at 0.01 was used. The R square values were all at 1.0. The regression results were:

$$\begin{aligned} D_r &= -0.05886 + 0.53052 R - 0.00002 R^5 \\ D_g &= -0.05253 + 0.37064 G - 0.00163 G^3 + 0.00005 G^5 \\ D_b &= -0.04136 + 0.37487 B + 0.00788 B^2 - 0.00007 B^5 \\ \text{where } R &= \ln(d_r / (2^8 - 1)), \\ G &= \ln(d_g / (2^8 - 1)), \\ B &= \ln(d_b / (2^8 - 1)), \end{aligned}$$

d_r , d_g and d_b are the red, green, and blue digital counts for 8-bit scan. The fact that the constant terms are significant might suggest the existence of the dark current for every channel. These regression formulae translate scanner red, green and blue digital counts of each patch to the transformed digital readings, D_r , D_g and D_b . An example of the linearization results is shown in Fig. 5.3-5 (c), where the transformed red digital counts (D_r) were plotted against their corresponding cyan concentrations.

Prior experiments on Ektachrome indicated that the non-linear 3 by 11 model performed better than the 3 by 3 linear model. Consequently, a 3 by 11 matrix based on the second order polynomial plus a $D_r * D_g * D_b$ cross term was used as the characterization model. Stepwise regression with forward selection (tolerance at 0.01) was used to derive the model coefficients of the independent variables (transformed digital readings, D_r , D_g and D_b) with the dependent variables (the predicted cyan, magenta and yellow concentrations). The regression results are summarized in Table XIII. The concentration differences between the model predictions and the actual concentrations are plotted against

actual concentrations as shown in Fig. 5.3-6. In general, the concentration differences are evenly distributed. However, there are unusual high concentration differences for the cyan and the magenta dyes in the medium density area. The sum of square errors in Table XIII also indicate that there were higher residual errors for the cyan and magenta dyes. It seems that the model did not explain the material property very well in that particular area.

FIG. 5.3-5. Example plots of cyan concentrations against (a) original (b) normalized and natural logarithm transformed (c) final linearized red scanner digital counts of Kodak Q-60C target's neutral patches.

TABLE XIII. Regression results of the 3 by 11 model (8-bit scan) for Q-60C target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
Constant	-0.010	Not Significant	Not Significant
D_r	1.361	-0.512	-0.181
D_g	-0.426	2.315	-0.802
D_b	Not Significant	-0.632	2.022
$D_r * D_g$	-0.191	0.094	-0.053
$D_r * D_b$	Not Significant	Not Significant	-0.042
$D_g * D_b$	Not Significant	0.074	-0.095
$D_r * D_g * D_b$	0.039	-0.072	0.055
D_r^2	0.062	Not Significant	Not Significant
D_g^2	Not Significant	Not Significant	0.050
D_b^2	Not Significant	Not Significant	0.069
R square value	0.999	0.999	1.000
S. S. Residual	0.161	0.177	0.075

The predicted concentrations from the 3 by 11 model were used to reconstruct the spectral reflectances of all the color patches with the prior derived eigenvectors and the base reflectance. The reconstructed spectral reflectance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and 2 degree observer. The average ΔE^*_{ab} color difference between the measured data and the 3 by 11 model's prediction is 0.89, with a maximum of 5.2 and the standard deviation of 0.67. The performance of the 3 by 11 model is further analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.3-7. The histogram of the ΔE^*_{ab} error is plotted in Fig. 5.3-8.

The highest ΔE^*_{ab} error is found from the first patch on the Q-60C target, which is a dark purple-blue color. Other high ΔE^*_{ab} errors are also found in the dark blue-red

region as shown in Fig. 5.3-7 (a) and (c). It seems that the model suffers more error in the low wavelength area, which is mainly related to the yellow concentration. However, the regression analysis indicated less residual error for the yellow dye than for the cyan dye or the magenta dye. Furthermore, these high ΔE^*_{ab} errors only happened in darker colors but not colors with high chroma as shown in Fig. 5.3-7 (b). These led to the conclusion that these errors are contributed by the interaction from the yellow dye with the cyan and the magenta dyes in the lower wavelength area and also by the higher quantization error in the 8-bit signal resolution. This is supported by the fact that there are secondary peaks in the cyan and the magenta eigenvectors in the lower wavelength area as shown in Fig. 5.3-2. In other words, the secondary absorption of the cyan dye or the magenta dye in the lower wavelength area resulted the model error. However, considering the fact 90% of the ΔE^*_{ab} errors are under 1.5 as shown in Fig. 5.3-8, the overall model performance is good.

Separate analysis was performed to verify the model performance on maintaining gray balance. Vector plots were generated using the measured L^* and C^*_{ab} values as the starting points and the predicted L^* and C^*_{ab} values as the ending points for the neutral patches as shown in Fig. 5.3-9 (a). The ΔC^*_{ab} were plotted against L^* as shown in Fig. 5.3-9 (b). The length of the vector on the Y-axis indicates the chroma shift from the measured data to the predicted data. The chroma shifts of these neutral patches by the model predictions are not as small as the transparent targets. The average ΔE^*_{ab} , ΔL^* , ΔC^*_{ab} , ΔH^*_{ab} between the measured and predicted data of the neutral patches were 0.78, 0.30, 0.40 and 0.52, respectively. This 3 by 11 non-linear model does not preserve gray balance entirely. Vector plots on a^* and b^* coordinates as well as Δa^* and Δb^* coordinates were generated for every other color of the cyan, magenta, yellow, red, green and blue ramps to show the hue shift from measured to predicted data in Fig. 5.3-10 (a) and (b).

FIG. 5.3-6. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 11 model (8-bit scan) for Kodak Q-60C target.

FIG. 5.3-7. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (8-bit scan) for Kodak Q-60C target.

FIG. 5.3-8. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for 8-bit scan under illuminant D50 for Kodak Q-60C target.

FIG. 5.3-9. Vector plots of the chroma shift (a) between L^* and C^*_{ab} (b) between L^* and ΔC^*_{ab} from measured and model predictions of the Kodak Q-60C target's neutral tones.

(a)

(b)

FIG. 5.3-10. Vector plots: (a) between a^* and b^* , (b) between Δa^* and Δb^* of the measured and predicted data of the Kodak Q-60C target's c, m, y, r, g, and b ramps.

5.3.5 Performance Verification

An independent 4X5 negative film was exposed with a CRT-based film recorder using a digital image with a 6x6x6 factorial design sampling and 18 levels of neutral patches. The negative film was processed at the R.I.T. photo processing lab with regular C-41 processing. A 5X7 print was generated from this 4x5 color negative on Kodak Ektacolor paper. The color patches on this print were spectrally measured and then independently scanned in 8-bit mode with the same setting as for the Q-60C target.

The averaged 8-bit scanner digital readings for each color patch were processed through the linearization equations and then the 3x11 model to get the predicted concentrations. The concentrations were then used to calculate the spectral property of each color patch with the prior derived eigenvectors as well as with the paper base reflectance. The resulting spectral reflectance curves were then used to calculate tristimulus values and

CIELAB values for illuminant D50 and 2 degree observer. The average color difference between the measured data and the model predictions was $2.09 \Delta E^*_{ab}$ unit, with standard deviation of 1.02. The maximum color difference was at 7.29. The histogram of the color difference resulting from the scanner calibration model is shown in Fig. 5.3-11. It is noticed that 93% of the model errors for this independent test target are under ΔE^*_{ab} of 3.5. The average color difference error from the independent test target is about 2 times more from the modeling target. The ΔE^*_{ab} differences are plotted against L^* , C^*_{ab} and h_{ab} respectively in Fig. 5.3-12 to show the normality of the model error. The scanner characterization model worked considerably well given the possible variance introduced from different batch of paper or different line of paper processing or the repeatability of the spectrophotometer.

FIG. 5.3-11. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for an independent Ektacolor target in 8-bit scan.

FIG. 5.3-12. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (8-bit scan) for independent Ektacolor paper target.

5.4 Opaque Material - Fuji Fujicolor Paper

A Fuji IT8.7/2 5X7 reflection target was used as the target object. The material base of this target is Fujicolor professional paper. The spectral data of each color patch on the Fuji IT8.7/2 target were measured by a Gretag SPM-60 spectrophotometer and recorded in the order as described in the experimental design section. The spectral data of all 288 patches from 390 nm to 730 nm at 10 nm increment were collected. The measurement was performed at the Munsell Color Science Laboratory.

5.4.1 Material Analysis

The first step in the material analysis was to determine the base reflectance, $R_g(\lambda)$, of the spectral model in Eq. (18). According to the IT8 specification, the minimum density (D-min, the maximum reflectance that a photographic paper can achieve) of the material is located at the lower-left corner on the target. A global search of all reflectance in every measured wavelength was performed and revealed that the maximum reflectance is not always found in the designated D-min patch. The global maximum reflectance and the reflectance of the D-min patch are shown in Fig. 5.4-1. The global maximum reflectance of every wavelength was taken as the material's base reflectance, $R_g(\lambda)$. Data can be found in Appendix B.

FIG. 5.4-1. Reflectance of the D-min patch (dashed line) and the global maximum reflectance (solid line) of the Fuji IT8.7/2 target.

After removing the base reflectance by dividing $R_g(\lambda)$ from every i th patch's spectral data, $R_i(\lambda)$, and transforming it with a natural logarithm function, the overall absorptivity, $K_i(\lambda)$, of the three dyes for the i th color was obtained as follow:

$$K_i(\lambda) = \ln(R_i(\lambda) / R_g(\lambda)) / -2.0$$

where $K_i(\lambda) = c_{ic} k_c(\lambda) + c_{im} k_m(\lambda) + c_{iy} k_y(\lambda)$. The c_{ic} , c_{im} and c_{iy} are the concentrations, and $k_c(\lambda)$, $k_m(\lambda)$ and $k_y(\lambda)$ are the unit spectral absorptivities of the cyan, magenta, and yellow dyes, respectively.

With all $K_i(\lambda)$ of each color patch, the unit absorptivity for each dye was analyzed with the principal component analysis of the SYSTAT statistics software package.³⁰ A

covariance matrix with the "equamax" rotation was used to estimate the three eigenvectors. These eigenvectors were considered as the global eigenvectors since they represented the overall gamut variance among all the color patches. The first three eigenvectors explained variances of 45.845%, 26.611%, and 26.480%, respectively. With a total of 99.936% explained by the first three eigenvectors, these three primary absorptivities described the paper characteristics quite well. The results of this analysis are summarized in Table XIV.

Three principal component analyses on the $K_i(\lambda)$ values of each cyan, magenta and yellow color ramp were performed respectively with covariance matrix form without any rotation. These ramps are located on the 13th, 14th and 15th columns of the IT8.7/2 target. The results of the analyses are also summarized in Table XIV. As expected, most of the variance in each analysis was explained by the first eigenvector, which implied the unit absorptivity of the cyan, magenta and yellow dye, respectively. Note that all the first eigenvectors from each of the cyan, magenta and yellow column did not totally explain the variance for each color, which suggests that these colors were not formed by a single dye. Since the first three eigenvectors accounted for 99.9% of the total variance, it confirms that three primaries are sufficient to represent the material's spectral characteristics.

TABLE XIV. Principal component analysis results: percentage of variance explained by the eigenvectors of Fuji IT8.7/2 target.

Sampling population (size)	Explained by 1st eigenvector	Explained by 2nd eigenvector	Explained by 3rd eigenvector	Total
All patches (288)	45.845%	27.611%	26.480%	99.936%
Cyan ramp (12)	99.921%	0.075%	0.002%	99.998%
Magenta ramp (12)	99.929%	0.057%	0.010%	99.995%
Yellow ramp (12)	99.472%	0.380%	0.143%	99.995%

Three linear regressions were further performed to rotate the three global eigenvectors to the vector spaces formed by the three color ramps. The three global eigenvectors were used as the independent variables and each of the first ramp eigenvector was used as the dependent variable respectively. There was no constant term in the regression since no offset was involved. All the terms were significant with the 2-tail P value less than 0.01. The regression results are summarized in Table XV. Based on the estimated cyan, magenta and yellow eigenvectors from the regression, the unit absorptivities of the Fujicolor professional paper are revealed as shown in Fig. 5.4-2 and the actual numbers are listed in Appendix B for reference. Note that, these absorptivity units were based on the natural logarithm in stead of the traditional 10 based log.

TABLE XV. Regression results: ramp eigenvectors against global eigenvectors for Fuji IT8.7/2 target.

Equation term	Coefficients for cyan ramp	Coefficients for magenta ramp	Coefficients for yellow ramp
global cyan	1.077	-0.300	-0.173
global magenta	0.075	1.230	-0.081
global yellow	0.023	-0.191	0.880
R square values	1.00	0.998	0.999
S.S. residual	0.003	0.005	0.001

FIG. 5.4-2. (a) Global eigenvectors (solid line) and eigenvectors from cyan, magenta and yellow ramps (dashed line) of Fuji IT8.7/2 target. (b) Final rotated eigenvectors of Fuji IT8.7/2 target.

5.4.2 Prediction of Actual Concentrations

With the rotated eigenvectors, a C program was used to predict the concentrations of the three dyes to yield tristimulus matches for each color patch (without the base reflectance, R_g). The tristimulus matches were performed for illuminant D50 first. If the eigenvectors are faithful to the absorptive properties of the film and if the Kubelka-Munk theory holds, the tristimulus matches will agree with spectral matches. Further verification was done by calculating color differences between the measured and the predicted spectra from a spectrally dissimilar light source, in this case illuminant A. Color differences for illuminant A were calculated as an index of metamerism; the average was 0.3 (maximum at 1.3) and the histogram is plotted in Fig. 5.4-3. This maximum is higher than the maximum of the transparent material, which implies that the Kubelka-Munk theory does not model the photographic paper as well as the Beer-Bouguer theory for the transparent film.

FIG. 5.4-3. Histogram of color differences for illuminant A between measured and predicted spectra by means of the tristimulus matching algorithm under illuminant D50 for Fuji IT8.7/2 target.

5.4.3 Image Scanning

A C program was implemented to gather direct red, green and blue scanner readings for the opaque materials. However due to a problem (documented in Appendix F) in the scanner system, the scanning of the photographic paper target was limited to the 8-bit mode only. The log scanning mode was used to replace the natural logarithm transformation in the linearization process. All the internal look-up tables were set as linear. The scanning resolution was set at 500 dpi.

In the image file, there were about 20,000 8-bit pixels per red, green and blue channel for each color patch and more for the bottom neutral patches. The exact digital counts were from the average of the center 3600 pixels of each color patch. The digital counts were normalized by 255 to confine the range to between 0 and 1.

5.4.4 Building Characterization Model

The linearization process was performed to find a linear relationship between concentrations of the Fuji IT8.7/2 target's neutral patches against their corresponding 8-bit red, green, and blue raw scanner digital counts (denoted d_r , d_g and d_b). Based on Eq. (29), it was expected that the digital counts from the log scan mode should be approximately linear to the concentration. Fig. 5.4-4 (a) is an example plot to show the relationship between the scanner red digital counts (d_r) and the corresponding cyan concentrations (C_c) of the Fuji IT8.7/2 target. Fig. 5.4-4 (b) shows the relationship between the normalized red digital counts and the cyan concentrations. From the straight slopes in both Figs. 5.4-4 (a) and (b), one can conclude that the natural logarithm transformation can be replaced by the log scan operation of the scanner.

The complete linearization process was performed by regressing the concentrations of the neutral patches of the Fuji IT8.7/2 target against their corresponding 8-bit r, g, and b digital counts (denoted d_r , d_g and d_b) with a fifth order polynomial equation. A forward stepwise model with a tolerance at 0.01 was used. The R square values were all at 1.0.

The regression results were:

$$D_r = 7.77771 - 7.86432 R$$

$$D_g = 8.52629 - 8.66417 G$$

$$D_b = 10.65026 - 10.08884 B - 0.63364 B^5$$

$$\text{where } R = d_r / (2^8 - 1),$$

$$G = d_g / (2^8 - 1),$$

$$B = d_b / (2^8 - 1),$$

d_r , d_g and d_b are the red, green, and blue digital counts for 8-bit log scan. The fact that the constant terms are significant might suggest the existence of the dark current for every channel. These regression formulae translate scanner red, green and blue digital counts of each patch to the transformed digital readings, D_r , D_g and D_b . An example of the linearization results is shown in Fig. 5.4-4 (c), where the transformed red digital counts (D_r) were plotted against their corresponding cyan concentrations.

FIG. 5.4-4. Example plots of cyan concentrations against (a) 8-bit log scanned (b) normalized (c) final linearized red digital counts of Fuji IT8.7/2 target's neutral patches.

A non-linear stepwise regression model was used to relate the transformed digital readings to the concentrations. The non-linear model included a 3 by 11 matrix based on the second order polynomial plus a $D_r \cdot D_g \cdot D_b$ cross term. Stepwise regression with forward selection (tolerance at 0.01) was used to derive the model coefficients of the independent variables (transformed digital readings, D_r , D_g and D_b) with the dependent variables (the predicted cyan, magenta and yellow concentrations). The regression results are summarized in Table XVI. The concentration differences between the model predictions and the actual concentrations are plotted against actual concentrations as shown in Fig. 5.4-5. In general, the concentration differences are evenly distributed, except the overall concentration differences are higher for the yellow dye. The sum of square residual is also higher for the yellow dye in the regression analysis as indicated in Table XVI. The secondary peak of the cyan eigenvector in the lower wavelength as shown in Fig. 5.4-2 (b) may cause the lack of model accuracy for the yellow dye.

TABLE XVI. Regression results of the 3 by 11 model (8-bit scan) for Fuji IT8.7/2 target.

Equation term (independent variable)	Coefficients for predicted cyan concentration	Coefficients for predicted magenta concentration	Coefficients for predicted yellow concentration
Constant	0.010	0.047	-0.032
D_r	1.044	-0.351	-0.348
D_g	-0.091	1.132	-0.415
D_b	-0.102	-0.250	1.097
$D_r * D_g$	-0.034	-0.021	0.030
$D_r * D_b$	Not Significant	-0.015	0.024
$D_g * D_b$	Not Significant	-0.016	Not Significant
$D_r * D_g * D_b$	Not Significant	0.005	-0.008
D_r^2	0.018	0.012	-0.016
D_g^2	0.010	0.008	Not Significant
D_b^2	Not Significant	0.006	0.009
R square value	1.000	0.999	0.999
S. S. Residual	0.062	0.110	0.262

FIG. 5.4-5. Concentration differences between predicted and actual (a) cyan, (b) magenta and (c) yellow dyes from the 3 by 11 model (8-bit scan) for Fuji IT8.7/2 target.

The predicted concentrations from the 3 by 11 model were used to reconstruct the spectral reflectances of all the color patches with the prior derived eigenvectors and the base reflectance. The reconstructed spectral reflectance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and the 2 degree observer. The average ΔE^*_{ab} color difference between the measured data and the 3 by 11 model's prediction is 0.88, with a maximum of 3.42 and the standard deviation of 0.48. The histogram of the ΔE^*_{ab} error is plotted in Fig. 5.4-6. The performance of the 3 by 11 model is further analyzed by plotting ΔE^*_{ab} against L^* , C^*_{ab} and h_{ab} in Fig. 5.4-7.

FIG. 5.4-6. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for 8-bit scan under illuminant D50 for Fuji IT8.7/2 target.

FIG. 5.4-7. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (8-bit scan) for Fuji IT8.7/2 target.

As shown in Fig. 5.4-7, this non-linear model does not induce higher error in the high chroma region; however, it shows more error in the low chroma region. This implies that when the dyes are mixed the higher error happens. This trend was also found in the Q-60C paper target. The higher errors are located around the blue-green hue as shown in Fig. 5.4-7 (c). The lack of accuracy in predicting the yellow concentration eventually translates into color error in the lower wavelength area, like the blue colors. However, considering the fact that 92% of the ΔE^*_{ab} errors are under 1.5 and the average ΔE^*_{ab} error is 0.9, the overall model performance is good.

Separate analysis was performed to verify the model performance on maintaining gray balance. Vector plots were generated using the measured L^* and C^*_{ab} values as the starting points and the predicted L^* and C^*_{ab} values as the ending points for the neutral patches as shown in Fig. 5.4-8 (a). The ΔC^*_{ab} values were also plotted against L^* as shown in Fig. 5.4-8 (b). The length of the vector on the Y-axis indicates the chroma shift from the measured data to the predicted data. As shown in Figs. 5.4-8 (a) and (b), the model introduced more chroma shift in the higher lightness area. These chroma shifts in the neutral patches of the Fuji IT8.7/2 target are higher than found in the transparent targets. The average ΔE^*_{ab} , ΔL^* , ΔC^*_{ab} , ΔH^*_{ab} between the measured and predicted data of the neutral patches were 0.58, 0.29, 0.36 and 0.19, respectively. This 3 by 11 non-linear model does not preserve gray balance entirely. Vector plots on a^* and b^* coordinates as well as Δa^* and Δb^* coordinates were generated for every other color of the cyan, magenta, yellow, red, green and blue ramps to show the hue shift from the measured to the predicted data in Fig. 5.4-9 (a) and (b).

(a)

(b)

FIG. 5.4-8. Vector plots of the chroma shift (a) between L^* and C^*_{ab} , (b) between L^* and ΔC^*_{ab} from measured and model predictions of the Fuji IT8.7/2 target's neutral tones.

(a)

(b)

FIG. 5.4-9. Vector plots: (a) between a^* and b^* , (b) between Δa^* and Δb^* of the measured and predicted data of the Fuji IT8.7/2 target's c, m, y, r, g, and b ramps.

5.4.5 Performance Verification

An independent 4X5 negative film was exposed with a CRT-based film recorder using a digital image with a 6x6x6 factorial design sampling and 18 levels of neutral patches. The negative film was processed at the R.I.T. photo processing lab with regular C-41 processing. A 5X7 print was generated from this 4x5 color negative on Fujicolor professional paper (medium contrast type). The color patches on this print were spectrally measured and then independently scanned in 8-bit log mode with the same setting as for the Fuji IT8.7/2 target.

The 8-bit scanner digital readings for each color patch were processed through the linearization equations and then the 3x11 model to get the predicted concentrations. The concentrations were then used to back calculate the spectral property of each color patch with the prior derived eigenvectors as well as with the Fuji IT8.7/2 target's base reflectance. The resulting spectral reflectance curves were then used to calculate tristimulus values and CIELAB values for illuminant D50 and 2 degree observer. The average color difference between the measured data and the model predictions was $8.8 \Delta E^*_{ab}$ unit, with the standard deviation of 3.6. The maximum color difference was at 21.3. The histogram of the color difference resulting from the scanner calibration model is shown in Fig. 5.4-10. The ΔE^*_{ab} differences are plotted against L^* , C^*_{ab} and h_{ab} , respectively in Fig. 5.4-11. These ΔE^*_{ab} errors are much higher than all the previous results. Even though the errors in yellow hue area are higher as shown in Fig. 5.4-11 (c), the overall errors are all quite large. However, no particular trend can be found in Fig. 5.4-11 to explain the large errors. The predicted spectral curves of three color patches (cyan, magenta and yellow) are plotted (in dashed lines) against the measured spectral curves (in solid lines) in Fig. 5.4-12.

In general, the predicted spectral data are smaller than the measured data and the curve shapes are similar but not parallel to each other. One exception is found in the magenta color, where the predicted curve has much higher secondary peak at 430 nm than the measured curve. It is suspected that the material property of this independent Fujicolor paper target is different from the standard Fuji IT8.7/2 target.

FIG. 5.4-10. Histogram of color differences between measured and predicted spectra by means of the 3 by 11 model for an independent Fuji Ektachrome target in 12-bit scan.

FIG. 5.4-11. Color differences versus (a) L^* , (b) C^*_{ab} and (c) h_{ab} from the 3 by 11 model predictions (8-bit scan) for an independent Fujicolor paper target.

FIG. 5.4-12. Spectral reflectances of measured (solid lines) and predicted (dashed lines) of (a) cyan, (b) magenta and (c) yellow colors from the independent Fujicolor test target for illuminant D50.

Further material analysis was performed on the independent Fujicolor target. The first step was to compare the base reflectance, $R_g(\lambda)$, of the independent target with the standard Fuji IT8.7/2 target. The base reflectance of the independent target (solid line) and the Fuji IT8.7/2 target (dashed line) is shown in Fig. 5.4-13. Clearly, the base reflectance of the IT8.7/2 target used in reconstructing the spectral curves is lower than that of the independent target except at around 430 nm. It explains why the model is under predicting the spectral data as shown in Fig. 5.4-12. With the independent target's base reflectance, the construction of the spectral data was performed with the IT8.7/2 target's eigenvectors. The average ΔE^*_{ab} color difference between the measured data and the recalculated data was 8.6, with a maximum of 21.0, which shows modest improvement. It is clear that the base reflectance difference could explain some but not all of the model error.

FIG. 5.4-13. Base reflectances of the Fujicolor independent target (solid line) and the Fuji IT8.7/2 target (dashed line).

A global eigenvector analysis was also performed on the independent target. After removing the base reflectance by dividing $R_g(\lambda)$ of the independent paper target from every patch's spectral data, $R_i(\lambda)$, and transforming it with a natural logarithm function, all absorptivities of the independent paper target were analyzed with the principal component analysis of the SYSTAT statistics software package. A covariance matrix with the "equamax" rotation was used to estimate the three eigenvectors. The first three eigenvectors accounted for the variances of 56.616%, 23.154% and 20.064%, respectively. The overall variance explained by these three eigenvectors was 99.835%, which is not as high as for the IT8.7/2 target.

Further statistical analysis was performed to assure that the difference is not caused by the rotation in the principal component analysis, which is similar to the rotation existed between the global and the ramp eigenvectors. Three stepwise regressions were performed using the independent target's eigenvectors as the dependent variables respectively and the IT8.7/2 target's eigenvectors as the independent variables. The tolerance was set at 0.01. The regression results are summarized in Table XVII. The estimated eigenvectors and the IT8.7/2 target's eigenvectors are plotted in Fig. 5.4-14 with solid lines and dashed lines, respectively. Comparing the results listed in Table XV and Table XVII, one can find that the regression results in Table XVII not only show smaller R square values but also indicate larger sum of square residuals, which indicates dissimilarity among the eigenvectors. According to the regression results, the most significant difference appears in the magenta eigenvector, which matches with the finding in Fig. 5.4-11 (c) that the yellow colors have higher model errors. The differences in curve shapes in Fig. 5.4-14 also indicate the dissimilarity among the eigenvectors. It is concluded that the material properties of the Fuji IT8.7/2 target and the independent Fujicolor paper target are not the

same. It explains why the color differences for the independent target were much larger than those of the modeling target. Since the spectral model is based on the reconstruction from the eigenvectors and the base reflectance, a consistent material property is essential to ensure the accuracy of this spectral model.

TABLE XVII. Regression results: the independent Fujicolor target's eigenvectors against the Fuji IT8.7/2 target's eigenvectors .

Equation term (independent variable) eigenvector of Fuji IT8.7/2 target	Coefficients for independent target's cyan eigenvector	Coefficients for independent target's magenta eigenvector	Coefficients for independent target's yellow eigenvector
cyan	1.080	0.119	Not Significant
magenta	-0.210	0.989	0.048
yellow	-0.238	Not Significant	0.983
R square values	0.999	0.995	0.996
S.S. residual	0.010	0.017	0.007

FIG. 5.4-14. Rotated eigenvectors of the independent Fujicolor target (solid line) and the eigenvectors of the Fuji IT8.7/2 target (dashed line).

6. Conclusions

A scanner characterization process based on an analytical spectral model was conducted in this thesis. Beer-Bouguer and Kubelka-Munk theories were the bases of the spectral models. The standard IT8.7 type transparent and opaque photographic targets were used in deriving the characterization model. Independent test targets were implemented to verify the model performance. The results of the characterization methods are summarized in Table XVIII.

TABLE XVIII. Summary of the scanner characterization results.

Material type	Ektachrome film	Fujichrome film	Ektacolor Plus paper	Fujicolor paper
Modeling target	Kodak IT8.7/1	Fuji IT8.7/1	Kodak Q-60C	Fuji IT8.7/2
Avg. ΔE^*_{ab} of modeling target	0.37	0.41	0.89	0.88
Max. ΔE^*_{ab} of modeling target	1.03	1.57	5.17	3.42
Avg. ΔE^*_{ab} of independent target	0.71	0.67	2.09	8.75
Max. ΔE^*_{ab} of independent target	1.78	1.56	7.29	21.3

The overall model performance of the transparent materials is better than that of the opaque materials. This may be due to the following factors:

- The Kubelka-Munk theory does not perfectly model the spectral property of photographic paper.
- Spectral bandwidths of the dyes in photographic paper are wider than transparent material and as a result, the scanner has difficulty in separating the colorants.
- The use of higher signal resolution (8-bit verse 12-bit) reduces the amount of quantization error.

In general, the spectral property of transparent materials follows the Beer-Bouguer theory better than the opaque material with the Kubelka-Munk theory. Perhaps, the refractive index assumption is not elaborate enough to describe the photographic opaque material and more complicated model is needed. Berns²⁸ found that for thermal paper, the Fresnel equation was necessary to correct the refractive index discontinuity.

Principal component analysis was shown as an excellent technique for deriving a material's dye absorptivities. A tristimulus matching method was applied and obtained satisfactory results in predicting dye concentrations. Theoretically, scanner digital counts could be related to dye concentrations with linear functions if the scanner's sensor responsivities are narrow. However, it was concluded that non-linear functions were necessary in modeling the scanner digital counts of the Howtek D4000 drum scanner to dye concentrations. In other words, non-linear models were needed to describe the functions between integral densities and analytic densities in this case. It was found that using the higher color resolution (12-bit) had better model performance than using the regular 8-bit color resolution. Furthermore, the performance improvement between using the non-linear model and using the linear model was more significant than that between using the 12-bit color resolution and using the 8-bit color resolution. In addition, the consistency of material property was crucial to the success of this spectral model application. When the object material is different from the material used for deriving the characterization model, this spectral model worked poorly. This factor should be taken into consideration in implementing a real product.

The overall objective of this thesis was to achieve colorimetric characterization of the Howtek D4000 drum scanner. By applying the characterization method described in this thesis, the average ΔE^*_{ab} error of less than 1.0 unit was achieved for the modeling targets. The average ΔE^*_{ab} error for independent targets was kept under the perceptibility threshold. The gray balance was also maintained for the neutral tones. Similar colorimetric accuracy was achieved for a theoretical simulation model^{13,14}; it is yet to be demonstrated in practice.

With characterization error within such a small range, a drum scanner could serve as a precise image input device. The results in this thesis show promising potential in the desk top color reproduction system. Future researches could focus on topics relying on precise input device, for example, a complete reproduction cycle from photographic original to digital printer output.

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Appendix A

Spectral Weights for Calculating Tristimulus Values

Spectral weights for illuminant D50 and 2 degree observer for calculating tristimulus values at 10 nm interval (data from ANSI CGATS.5-1993).

Wavelength (nm)	W(X)	W(Y)	W(Z)
360	0.000	0.000	0.001
370	0.001	0.000	0.005
380	0.003	0.000	0.013
390	0.012	0.000	0.057
400	0.060	0.002	0.285
410	0.234	0.006	1.113
420	0.775	0.023	3.723
430	1.610	0.066	7.862
440	2.453	0.162	12.309
450	2.777	0.313	14.647
460	2.500	0.514	14.346
470	1.717	0.798	11.299
480	0.861	1.239	7.309
490	0.283	1.839	4.128
500	0.040	2.948	2.466
510	0.088	4.632	1.447
520	0.593	6.587	0.736
530	1.590	8.308	0.401
540	2.799	9.197	0.196
550	4.207	9.650	0.085
560	5.657	9.471	0.037
570	7.132	8.902	0.020
580	8.540	8.112	0.015

590	9.255	6.829	0.010
600	9.835	5.838	0.007
610	9.469	4.753	0.004
620	8.009	3.573	0.002
630	5.926	2.443	0.001
640	4.171	1.629	0.000
650	2.609	0.984	0.000
660	1.541	0.570	0.000
670	0.855	0.313	0.000
680	0.434	0.158	0.000
690	0.194	0.070	0.000
700	0.097	0.035	0.000
710	0.050	0.018	0.000
720	0.022	0.008	0.000
730	0.012	0.004	0.000
740	0.006	0.002	0.000
750	0.002	0.001	0.000
760	0.001	0.000	0.000
770	0.001	0.000	0.000
780	0.000	0.000	0.000
Sums	X = 96.421	Y = 99.997	Z = 82.524

Appendix B

Spectral Property of the Target Materials

(a) Kodak IT8.7/1 target (Kodak Professional Ektachrome 100 Plus film)

Wavelength (nm)	Base transmittance	Cyan eigenvector	Magenta eigenvector	Yellow eigenvector
390	0.050	0.264	0.257	0.541
400	0.126	0.195	0.180	0.790
410	0.364	0.155	0.195	0.995
420	0.512	0.131	0.225	1.173
430	0.556	0.112	0.267	1.317
440	0.587	0.096	0.279	1.401
450	0.611	0.084	0.266	1.412
460	0.628	0.075	0.281	1.338
470	0.642	0.071	0.331	1.177
480	0.654	0.073	0.412	0.960
490	0.660	0.079	0.527	0.728
500	0.660	0.090	0.678	0.518
510	0.660	0.108	0.863	0.350
520	0.658	0.131	1.057	0.229
530	0.648	0.163	1.224	0.149
540	0.647	0.203	1.333	0.101
550	0.647	0.253	1.370	0.073
560	0.641	0.313	1.329	0.056
570	0.642	0.386	1.202	0.045
580	0.656	0.475	1.001	0.035
590	0.680	0.578	0.766	0.029
600	0.689	0.688	0.557	0.024
610	0.687	0.799	0.400	0.021
620	0.681	0.904	0.292	0.020
630	0.674	0.992	0.222	0.019
640	0.667	1.054	0.176	0.019
650	0.661	1.089	0.146	0.018
660	0.657	1.093	0.125	0.019
670	0.656	1.070	0.109	0.018
680	0.656	1.021	0.097	0.016
690	0.662	0.949	0.087	0.016
700	0.665	0.859	0.077	0.014
710	0.677	0.757	0.067	0.013
720	0.680	0.650	0.058	0.012
730	0.699	0.558	0.050	0.011

(b) Fuji IT8.7/1 target (Fujichrome 100 Professional D film)

Wavelength (nm)	Base transmittance	Cyan eigenvector	Magenta eigenvector	Yellow eigenvector
390	0.064	0.308	0.250	0.611
400	0.252	0.231	0.168	0.844
410	0.473	0.172	0.208	1.070
420	0.528	0.131	0.252	1.289
430	0.534	0.103	0.309	1.458
440	0.549	0.081	0.336	1.554
450	0.577	0.063	0.324	1.573
460	0.595	0.052	0.352	1.491
470	0.613	0.050	0.429	1.300
480	0.631	0.056	0.549	1.045
490	0.646	0.070	0.714	0.777
500	0.654	0.091	0.919	0.537
510	0.654	0.121	1.144	0.349
520	0.648	0.158	1.353	0.217
530	0.637	0.205	1.507	0.132
540	0.625	0.263	1.578	0.080
550	0.609	0.336	1.565	0.049
560	0.593	0.424	1.466	0.030
570	0.596	0.531	1.291	0.016
580	0.619	0.655	1.060	0.007
590	0.658	0.802	0.804	0.000
600	0.674	0.963	0.565	-0.005
610	0.682	1.124	0.383	-0.010
620	0.682	1.271	0.258	-0.014
630	0.679	1.401	0.170	-0.015
640	0.675	1.498	0.112	-0.016
650	0.668	1.557	0.076	-0.018
660	0.660	1.576	0.052	-0.018
670	0.656	1.556	0.035	-0.016
680	0.658	1.495	0.026	-0.018
690	0.661	1.396	0.018	-0.016
700	0.675	1.266	0.014	-0.014
710	0.693	1.112	0.010	-0.013
720	0.701	0.947	0.009	-0.010
730	0.720	0.787	0.009	-0.007

(c) Kodak Q-60C target (Kodak Ektacolor paper)

Wavelength (nm)	Base reflectance	Cyan eigenvector	Magenta eigenvector	Yellow eigenvector
390	0.018	0.191	0.081	0.178
400	0.112	0.301	0.146	0.365
410	0.313	0.330	0.192	0.504
420	0.644	0.328	0.237	0.631
430	0.775	0.296	0.256	0.696
440	0.812	0.260	0.243	0.733
450	0.783	0.227	0.246	0.751
460	0.793	0.207	0.271	0.734
470	0.797	0.194	0.312	0.685
480	0.787	0.189	0.372	0.606
490	0.792	0.193	0.452	0.511
500	0.795	0.205	0.544	0.414
510	0.792	0.225	0.635	0.329
520	0.797	0.250	0.708	0.263
530	0.789	0.282	0.756	0.213
540	0.771	0.318	0.770	0.179
550	0.765	0.359	0.748	0.155
560	0.762	0.403	0.681	0.134
570	0.757	0.451	0.574	0.112
580	0.761	0.514	0.448	0.088
590	0.776	0.589	0.342	0.070
600	0.787	0.665	0.264	0.056
610	0.795	0.736	0.212	0.048
620	0.800	0.803	0.176	0.043
630	0.798	0.857	0.150	0.039
640	0.809	0.895	0.132	0.037
650	0.830	0.925	0.122	0.037
660	0.848	0.942	0.114	0.036
670	0.861	0.929	0.106	0.036
680	0.870	0.906	0.100	0.034
690	0.873	0.865	0.093	0.033
700	0.876	0.818	0.086	0.032
710	0.864	0.746	0.078	0.030
720	0.819	0.652	0.069	0.027
730	0.739	0.570	0.060	0.025

(d)Fuji IT8.7/2 target (Fujicolor paper)

Wavelength (nm)	Base reflectance	Cyan eigenvector	Magenta eigenvector	Yellow eigenvector
390	0.035	0.181	0.129	0.220
400	0.156	0.217	0.163	0.313
410	0.428	0.221	0.185	0.393
420	0.777	0.213	0.203	0.469
430	0.886	0.191	0.211	0.510
440	0.897	0.169	0.215	0.530
450	0.863	0.153	0.229	0.544
460	0.841	0.139	0.245	0.532
470	0.838	0.128	0.265	0.490
480	0.827	0.119	0.293	0.427
490	0.812	0.116	0.337	0.363
500	0.793	0.121	0.398	0.310
510	0.780	0.131	0.460	0.275
520	0.785	0.148	0.509	0.255
530	0.803	0.170	0.552	0.248
540	0.802	0.197	0.588	0.251
550	0.794	0.227	0.594	0.251
560	0.791	0.259	0.548	0.240
570	0.792	0.297	0.458	0.220
580	0.796	0.349	0.352	0.200
590	0.794	0.413	0.279	0.192
600	0.792	0.479	0.242	0.196
610	0.790	0.541	0.230	0.208
620	0.793	0.600	0.231	0.222
630	0.792	0.645	0.235	0.233
640	0.796	0.675	0.239	0.241
650	0.802	0.697	0.243	0.247
660	0.809	0.708	0.245	0.250
670	0.819	0.692	0.239	0.245
680	0.831	0.670	0.231	0.237
690	0.843	0.632	0.218	0.224
700	0.856	0.588	0.203	0.209
710	0.850	0.526	0.183	0.187
720	0.812	0.451	0.157	0.161
730	0.735	0.385	0.135	0.138

Appendix C

Program to Predict Concentrations

/*

Program to predict CMY concentrations of photographic material with the tristimulus matching algorithm. The CMY eigenvectors are used to match with the transmittance (or reflectance) of each test patch without the base white transmittance $T_g(\lambda)$. See section 3.2 of the thesis for complete description of the algorithm.

Author: R. S. Berns, March 1993

FORTTRAN vintage: tenured professor

ANSI C: Translated by Helen HaeKyung Shin, January 1994

Think C 6.0: Modified by M. J. Shyu, March 1994

Input files:

fp_target = fopen("target.dat", "r"); -- id, $T_i(\lambda)/T_g(\lambda)$ (λ : 390~730/++10);
fp_pc = fopen("pca.dat", "r"); -- (C, M, Y) eigenvectors (λ : 390~730/++10);
fp_d50 = fopen("d50_2deg_10nm.dat", "r"); -- ASTM weightings for d50;
fp_iA = fopen("ia_2deg_10nm.dat", "r"); -- ASTM CMF weightings for ill. A;

Output file:

fout = fopen("pred_cmyd50.res", "w"); -- id, dEillA, dEd50, c, m, y predictions.

SPECIAL NOTE:

Change TOTAL_NB when the number of patches in the target is different.
The input $T(\lambda)$ file has to be $T(\lambda)/T_g(\lambda)$ with the base white $T_g(\lambda)$ removed.
Number of wavelengths = 35 (390-730, 10++), change #define when needed.
Maximum number of images to be matched is 300.

*/

```
#define TOTAL_NB      264          /* Number of the test colors to be matched */
#define LOWER_WL      390          /* Wavelength measurement starts at */
#define UPPER_WL      730          /* Wavelength measurement ends at */
#define BANDWIDTH      10          /* Bandpass in the measurement */
#define NW_COUNT      (UPPER_WL - LOWER_WL) / 10 + 1
```

```
#define NR_END 1
#define FREE_ARG      char *
```

```
#include <stdio.h>
#include <math.h>
#include <stdlib.h>
#include <string.h>
```

```
double  **dmix, **tmix;
```

```

/***** Utility routines *****/

/* Append end-of-string char. */
void stripnl(str)
char *str;
{
    int i;

    i = strlen(str);
    str[i-1] = '\0';
}

void nerror(error_text)
char error_text[];
{
    fprintf(stderr, "%s\n", error_text);
}

/* Allocate a double vector with subscript range v[nl..nh]. */
double *dvector(nl, nh)
long nl, nh;
{
    double *v;

    v=(double *)malloc((size_t) ((nh-nl+1+NR_END)*sizeof(double)));
    if (!v) nerror("allocation failure in dvector()");
    return v-nl+NR_END;
}

/* Allocate a double matrix with subscript range m[nrl..nrh][ncl..nch]. */
double **dmatrix(nrl, nrh, ncl, nch)
long nrl, nrh, ncl, nch;
{
    long i, nrow=nrh-nrl+1, ncol=nch-ncl+1;
    double **m;

    /* allocate pointers to rows */
    m=(double **) malloc((size_t)((nrow+NR_END)*sizeof(double *)));
    if (!m) nerror("allocation failure 1 in matrix()");
    m += NR_END;
    m -= nrl;

    /* allocate rows and set pointers to them */
    m[nrl]=(double *) malloc((size_t)((nrow*ncol+NR_END)*sizeof(double)));
    if (!m[nrl]) nerror("allocation failure 2 in matrix()");
    m[nrl] += NR_END;
    m[nrl] -= ncl;

    for(i=nrl+1;i<=nrh;i++) m[i]=m[i-1]+ncol;

    /* return pointer to array of pointers to rows */
}

```

```

        return m;
    }

/* Free a double vector allocated with dvector(). */
void free_dvector(double *v, long nl, long nh)
{
    free((FREE_ARG) (v+nl-NR_END));
}

/* Free a double matrix allocated by dmatrix(). */
void free_dmatrix(double **m, long nrl, long nrh, long ncl, long nch)
{
    free((FREE_ARG) (m[nrl]+ncl-NR_END));
    free((FREE_ARG) (m+nrl-NR_END));
}

/* Matrix multiplication r = a*b. */
void gmprod(a, b, r, n, m, l)
double **a, **b, **r;
int n, m, l;
{
    int i, j, k;

    for (i = 1; i <= n; i++)
    {
        for (j = 1; j <= l; j++)
        {
            r[i][j] = 0.;
            for (k = 1; k <= m; k++)
            {
                r[i][j] += a[i][k] * b[k][j];
            }
        }
    }
}

/* Calculate tristimulus values with spectral model. */
void tri(nb, phi, conc, te, tsvd, tea, tsva)
int nb;
double **phi, **conc, **te, **tsvd, **tea, **tsva;
{
    int i, j;

    gmprod(phi, conc, dmix, nb, 3, 1);

    for (j = 1; j <= nb; j++)
    {
        tmix[j][1] = exp(-dmix[j][1]);
    }

    gmprod(te, tmix, tsvd, 3, nb, 1);
    gmprod(tea, tmix, tsva, 3, nb, 1);
}

```



```

}

/* Matrix inversion . */
void invert_mat(P)
double **P;
{
    double **wrk;
    int k, me, na;
    int i,j;

    wrk = dmatrix(1,3,1,1);

    for (me = 1; me <= 3; me++)
    {
        wrk[3][1] = (double)1. / (double)P[1][1];
        for (k = 2; k <= 3; k++)
        {
            wrk[k-1][1] = (double)P[1][k] / (double)P[1][1];
        }

        for (k = 1; k <= 2; k++)
        {
            P[k][3] = -P[k+1][1] * wrk[3][1];
            for (na = 1; na <= 2; na++)
            {
                P[k][na] = P[k+1][na+1] - P[k+1][1] * wrk[na][1];
            }
        }

        for (k = 1; k <= 3; k++)
        {
            P[3][k] = wrk[k][1];
        }
    }
    free_dmatrix(wrk,1,3,1,1);
}

```

```

/***** Main Program *****/
int main()
{
    double **P, **T, **Z;
    double **tmeas, *tin, **din, *nm;
    double **d, **ted, **tedphi, **phi, **te;
    double **conc, **tedf, **tstd, **tsvstd;
    double **deltat, **deltaconc;
    double **tea, **tsva, **dstd, **tsvd;
    double **tsvastd, **deigenvec, *wave;

    double ldmix, lamix, ldstd, lastd;
    char *names[300];
    char error_text[100];

    void invert_mat();

    int ncol = TOTAL_NB;
    int NW = NW_COUNT;

    int i, j, jj, j1, j2;
    double deamax, dedmax;
    int iter, icount = 0;
    double sum, fsum, adstd, bdstd, aastd, bastd, deavga, deavg,
    aamix, bamix, admix, bdmix, ded, dea, sumde, sumdea;

    int id; /* color id */

    FILE *fp_target, *fp_pc, *fp_d50, *fp3, *fp_iA, *fout;
    char buffer[500];

    dmix = dmatrix(1,NW,1,1);
    tmix = dmatrix(1,NW,1,1);

    /* allocate spaces for vectors */
    T = dmatrix(1,3,1,1);
    Z = dmatrix(1,3,1,1);
    tin = dvector(1,NW); /* Transmittance of the standard colors to be matched */
    nm = dvector(1,NW); /* predicted CMY concentrations */
    conc = dmatrix(1,3,1,1);
    tedf = dmatrix(1,3,1,1);
    deltat = dmatrix(1,3,1,1);
    deltaconc = dmatrix(1,3,1,1);
    dstd = dmatrix(1,NW,1,1); /* D matrix of Ill. D50 */
    tstd = dmatrix(1,NW,1,1); /* 2-D array of T standard */
    tsva = dmatrix(1,3,1,1); /* tristimulus from Illu. A */
    tsvd = dmatrix(1,3,1,1); /* tristimulus from Illu. D50 */
    tsvastd = dmatrix(1,3,1,1); /* tristimulus values of the standard under Ill A */
    tsvstd = dmatrix(1,3,1,1); /* tristimulus values of the standard under Ill D50 */
    wave = dvector(1,NW);

    /* allocate spaces for matrices */

```

```

P = dmatrix(1,3,1,3);
din = dmatrix(1,20,1,NW);
d = dmatrix(1,NW,1,NW);
ted = dmatrix(1,3,1,NW);
tedphi = dmatrix(1,3,1,3);
phi = dmatrix(1,NW,1,3);
te = dmatrix(1,3,1,NW);          /* ASTM weightings for Ill. D50 */
tea = dmatrix(1,3,1,NW);         /* ASTM weightings for Ill. A */
deigenvec = dmatrix(1,3,1,NW);

/* Open files */
fp_target = fopen("target.dat", "r");
fp_pc = fopen("pca.dat", "r");
fp_d50 = fopen("d50_2deg_10nm.dat", "r");
fp_iA = fopen("ia_2deg_10nm.dat", "r");
fout = fopen("pred_cmyd50.res", "w");

/*****
ASTM weightings, W matrix
*****/
/* read in CMF for D50 2 degree */
for (j = 1; j <= NW; j++)
{
    fscanf(fp_d50, "%lf", &(wave[j]));
    for (i = 1; i <= 3; i++)
    {
        fscanf(fp_d50, "%lf", &(te[i][j]));
    }
}

/* read in CMF for Ill A 2 degree */
for (j = 1; j <= NW; j++)
{
    fscanf(fp_iA, "%lf", &(wave[j]));
    for (i = 1; i <= 3; i++)
    {
        fscanf(fp_iA, "%lf", &(tea[i][j]));
    }
}

/*****
colorant data base calculations from eigenvectors, Phi matrix
*****/

/* read in eigenvectors, kc, km and ky */
for (j = 1; j <= NW; j++)
{
    for (i = 1; i <= 3; i++)
    {
        fscanf(fp_pc, "%lf", &(deigenvec[i][j]));
    }
}

```

```

/* calculate phi matrix */
for (i = 1; i <= 3; i++)
{
    for (j = 1; j <= NW; j++)
    {
        phi[j][i] = deigenvec[i][j]; /* transposed */
    }
}

/*****
loop for colors
*****/

deamax = 0.;
dedmax = 0.;
sumde = 0.;
sumdea = 0.;

for (i = 1; i <= ncol; i++)
{
    /* read in standard color's T() */
    fscanf(fp_target, "%d\t", &id);
    for (j = 1; j <= NW; j++)
    {
        fscanf(fp_target, "%lf\t", &(tin[j]));
    }

    /* calculate spectral densities */
    for (j = 1; j <= NW; j++)
    {
        dstd[j][1] = -log(tin[j]);
        tstd[j][1] = tin[j];
    }

    /* calculate d matrix (derivative matrix) */
    for (j1 = 1; j1 <= NW; j1++)
    {
        for (j2 = 1; j2 <= NW; j2++)
        {
            d[j1][j2] = 0.;
        }
    }
    for (j = 1; j <= NW; j++)
    {
        d[j][j] = - 2.3026 * tstd[j][1];
    }

    /* match for ill D50 */
    /* calc pseudo tsvs for colorant data and form 3*3 */
    gmprod(te, d, ted, 3, NW, NW);          /* WD */
    gmprod(ted, phi, tedphi, 3, NW, 3);      /* WDPhi */
}

```

```

invert_mat(tedphi);                                /* invt(WDPhi) */

gmprod(ted, dstd, tedf, 3, NW, 1);                 /* WDf */
gmprod(tedphi, tedf, conc, 3, 3, 1);               /* C = invt(WDPhi) WDf */

/* calculate tristimulus values of the standard */
gmprod(te, tstd, tsvstd, 3, NW, 1); /* for D50 */
gmprod(tea, tstd, tsvastd, 3, NW, 1); /* for Illu. A */

iter = 1;
while (1)
{
    tri(NW, phi, conc, te, tsvd, tea, tsva);

    /* calculate delta X, Y, Z by D50 optimization */
    for (j = 1; j <= 3; j++)
    {
        deltat[j][1] = tsvstd[j][1] - tsvd[j][1];
    }

    /* check for goodness */
    fsum = deltat[1][1] + deltat[2][1];
    fsum = fsum + deltat[3][1];
    /* make it into two lines to avoid think C compiler error !? */

    sum = fabs(fsum);
    if (sum < .0001) break;

    invert_mat(tedphi);                                /* invt(WDPhi) !! */
    gmprod(tedphi, deltat, deltaconc, 3, 3, 1);

    for (j = 1; j <= 3; j++)
    {
        conc[j][1] += deltaconc[j][1];
    }

    iter++;
}

/* calculate tsvs of final iteration */

tri(NW, phi, conc, te, tsvd, tea, tsva);

/* calculate CIELAB */
/* D50 */
ldstd = 116. * pow(tsvstd[2][1]/100., .333);
adstd = 500. * (pow(tsvstd[1][1]/96.42, .333) - pow(tsvstd[2][1]/100., .333));
bdstd = 200. * (pow(tsvstd[2][1]/100., .333) - pow(tsvstd[3][1]/82.49, .333));

ldmix = 116. * pow(tsvd[2][1]/100., .333);
admix = 500. * (pow(tsvd[1][1]/96.42, .333) - pow(tsvd[2][1]/100., .333));
bdmix = 200. * (pow(tsvd[2][1]/100., .333) - pow(tsvd[3][1]/82.49, .333));

```

```

/* Illuminant A */
lastd = 116. * pow(tsvastd[2][1]/100., .333);
aastd = 500. * (pow(tsvastd[1][1]/109.85, .333)-pow(tsvastd[2][1]/100., .333));
bastd = 200. * (pow(tsvastd[2][1]/100., .333) - pow(tsvastd[3][1]/35.58, .333));

lamix = 116. * pow(tsva[2][1]/100., .333);
aamix = 500. * (pow(tsva[1][1]/109.85, .333)-pow(tsva[2][1]/100., .333));
bamix = 200. * (pow(tsva[2][1]/100., .333) - pow(tsva[3][1]/35.58, .333));

ded = sqrt((ldmix-ldstd) * (ldmix-ldstd) +
            (admix-adstd) * (admix-adstd) +
            (bdmix-bdstd) * (bdmix-bdstd));

dea = sqrt((lamix-lastd) * (lamix-lastd) +
            (aamix-aastd) * (aamix-aastd) +
            (bamix-bastd) * (bamix-bastd));

sumde += ded;
sumdea += dea;

if (ded > dedmax)
{
    dedmax = ded;
}

if (dea > deamax)
{
    deamax = dea;
}

fprintf(fout,"%d %.4f %.4f %.4f %.4f\n", id, dea, ded, conc[1][1], conc[2][1],
        conc[3][1]);

    icount ++;
}

deavg = sumde / (double)icount;
deavga = sumdea / (double)icount;

fprintf(fout,"Average dE d50 %lf\n", deavg);
fprintf(fout,"Max dE d50 %lf\n", dedmax);
fprintf(fout,"Average dE illA %lf\n", deavga);
fprintf(fout,"Max dE illA %lf\n", deamax);
fprintf(fout,"icount %d\n", icount);

/* free double vectors allocated by dvector()
   free double matrix allocated by dmatrix() */

free_dmatrix(dmix,1,NW,1,1);
free_dmatrix(tmix,1,NW,1,1);
free_dmatrix(T,1,3,1,1);

```

```

free_dmatrix(Z,1,3,1,1);
free_dvector(tin,1,NW);
free_dvector(nm,1,NW);
free_dmatrix(conc,1,3,1,1);
free_dmatrix(tedf,1,3,1,1);
free_dmatrix(tsvstd,1,3,1,1);
free_dmatrix(deltat,1,3,1,1);
free_dmatrix(deltaconc,1,3,1,1);
free_dmatrix(tsva,1,3,1,1);
free_dmatrix(dstd,1,NW,1,1);
free_dmatrix(tstd,1,NW,1,1);
free_dmatrix(tsvd,1,3,1,1);
free_dmatrix(tsvstd,1,3,1,1);
free_dvector(wave,1,NW);
free_dmatrix(P,1,3,1,3);
free_dmatrix(din,1,20,1,NW);
free_dmatrix(d,1,NW,1,NW);
free_dmatrix(ted,1,3,1,NW);
free_dmatrix(tedphi,1,3,1,3);
free_dmatrix(phi,1,NW,1,3);
free_dmatrix(te,1,3,1,NW);
free_dmatrix(tea,1,3,1,NW);
free_dmatrix(deigenvec,1,3,1,NW);

fclose(fout);

```

Appendix D

Program to Calculate Color Difference

/*

Purpose:

Program to calculate color difference between the measured spectral data of the target object and the predicted spectral data. The predicted spectral data are calculated from the eigenvectors and the predicted concentrations with base reflectance (or transmittance) provided by the input files. ASTM weights for illuminant D50 and 2 degree observer are used for the computation.

Author:

M. J. Shyu

Input files:

filename: "R0.dat" - measured spectral data
format: id, $R_i(\lambda)$ (λ from 390~730/++10)
id = 0 is the reference white (base material)

filename: "pca.dat" - 3 columns of C, M, Y eigenvectors (390~730/++10)

filename: "cmy_conc.dat" - 3 columns of predicted C, M, Y concentrations

filename: "ASTM_Wd50.dat" - ASTM weights for d50

Output file:

filenames: "Lab_dE.res" - the computation results
format: id, dEillA, dEd50, c, m, y predictions

filename: "R_predicted.res" - predicted reflectance of the target object

Special Note:

Change TOTAL_NB when the number of patches in the target is different.
Number of wavelengths = 35 (390-730, 10++), change #define when needed.

*/

File “cie.h”

```
#include <stdio.h>
#include "math.h"

typedef struct CIEXYZ /* tristimulus value */
{
    double X;
    double Y;
    double Z;
};

typedef struct CHRO /* chromaticity value */
{
    double x;
    double y;
};

typedef struct CIELAB /* CIE Lab value */
{
    double L;
    double a;
    double b;
};

typedef struct CIELCH /* CIE LCH value */
{
    double L;
    double C;
    double H;
};
```

File “utilities.c”

```
#include <stdio.h>
#include "math.h"
#include "CIE.h"
#define PI 3.141592654
#define POW_P3(x) pow(x, 1.0 / 3.0) /* x ^ 1/3 */

/* This atan function returns unit in degree from input x and y values */
double MY_ATAN(y,x)
double y, x;
{
    double degree;

    if ( x == 0 )
        x = 0.0000000001; /* avoid divide by 0 */

    degree = atan2(y,x) * 180.0 / PI; /* atan2 return radian */

    if ( degree < 0 )
        degree = degree + 360.0;

    return(degree);
}

/* This functions returns LCh values from input Lab values */
int Lab_LabLCh(Lab, LCh)
struct CIELAB Lab;
struct CIELCH *LCh;
{
    extern double MY_ATAN();
    LCh->L = Lab.L;
    LCh->C = sqrt((Lab.a * Lab.a) + (Lab.b * Lab.b));
    LCh->H = MY_ATAN(Lab.b, Lab.a);
    return(0);
}

/* This function calculates tristimulus values from input spectral data with ASTM weights */
void get_XYZ(spe, W_CMF, tris)
double spe[];
double W_CMF[][3];
struct CIEXYZ *tris;
{
    int wv;

    tris->X = 0.0;
    tris->Y = 0.0;
    tris->Z = 0.0;

    for ( wv = 0; wv < NW; wv++)
    {
```

```

        tris->X += spe[wv] * W_CMF[wv][0];
        tris->Y += spe[wv] * W_CMF[wv][1];
        tris->Z += spe[wv] * W_CMF[wv][2];
    }
}

```

/* This program calculates Lab values from XYZ. For details see p. 66 Measuring Color by Bob Hunt.

```

*
* Input:
*     XYZ: test tristimulus value
*     XYZw: reference white's tristimulus value.
* Output:
*     *Lab.
*/

```

```

int XYZ_Lab(XYZ, XYZw, Lab)
struct CIEXYZ XYZ, XYZw;
struct CIELAB *Lab;
{
    double r_x, r_y, r_z;
    double r_x_f, r_y_f, r_z_f;

    r_x = XYZ.X / XYZw.X;
    r_y = XYZ.Y / XYZw.Y;
    r_z = XYZ.Z / XYZw.Z;

    if ( r_y > 0.008856 )
    {
        r_y_f = POW_P3(r_y);
        Lab->L = 116.0 * r_y_f - 16.0;
    }
    else
    {
        Lab->L = 903.3 * r_y;
        r_y_f = 7.787 * r_y + 16.0 / 116.0;
    }

    if ( r_x > 0.008856 )
    {
        r_x_f = POW_P3(r_x);
    }
    else
    {
        r_x_f = 7.787 * r_x + 16.0 / 116.0;
    }

    if ( r_z > 0.008856 )
    {
        r_z_f = POW_P3(r_z);
    }
    else
    {

```

```
        r_z_f = 7.787 * r_z + 16.0 / 116.0;  
    }  
  
    Lab->a = (r_x_f - r_y_f) * 500.0;  
    Lab->b = (r_y_f - r_z_f) * 200.0;  
  
    return(0);
```

File “main.c”

```
#include <stdio.h>
#include <math.h>
#include "CIE.h"

#define TOTAL_NB      264          /* Number of the test colors to be matched */
                                   /* 264 for IT8.7/1-2, 236 for Q60C, 234 for 666 target */
#define LOWER_WL      390          /* Wavelength measurement starts at */
#define UPPER_WL      730          /* Wavelength measurement ends at */
#define BANDWIDTH      10          /* Bandpass in the measurement */
#define NW              (UPPER_WL - LOWER_WL) / 10 + 1 /* number of wavelength ticks */

/***** Main Program *****/
int main()
{
    double base_white[NW], r_std[NW], r_pred[NW];
    double cmy_conc[3], vector[NW][3];
    int wave_pca[NW], wave_astm[NW];
    double W[NW][3];
    struct CIEXYZ white_ref, tris_std, tris_pred;
    struct CIELAB lab_std, lab_pred;
    struct CIELCH lch_std;
    double *ptr1, *ptr2;

    int      id_std, id_pred; /* color id */
    double k_sum = 0.0, dE[TOTAL_NB], dE_max = 0.0, dE_sum = 0.0, dE_avg;
    double dE_stddev, sum_msq = 0.0;
    int      i, j, k;
    int      count = 0;

    FILE      *fp_stdR, *fp_pc, *fp_conc, *fp_d50, *fout, *fp_rpred;

    /* Open files */
    fp_stdR = fopen("R0.dat", "r");
    fp_pc = fopen("pca.dat", "r");
    fp_conc = fopen("cmy_conc.dat", "r");
    fp_d50 = fopen("ASTM_Wd50.dat", "r");
    fout = fopen("Lab_dE.res", "w");
    fp_rpred = fopen("R_predicted.res", "w");

    /*****
    ASTM weights, D50 2 degree
    *****/
    /* read in W for D50 2 degree */
    white_ref.X = white_ref.Y = white_ref.Z = 0.0;
    for (i = 0; i < NW; i++)
    {
        fscanf(fp_d50, "%d", &(wave_astm[i]));
        for (j = 0; j < 3; j++)
        {
            fscanf(fp_d50, "%lf", &(W[i][j]));

```

```

    }
    white_ref.X += W[i][0];
    white_ref.Y += W[i][1];
    white_ref.Z += W[i][2];
}

/*****
colorant data base calculations: eigenvectors from PCA
*****/

/* read in eigenvectors, kc, km and ky */
for (i = 0; i < NW; i++)
{
    fscanf(fp_pc, "%d", &(wave_pca[i]));
    for (j = 0; j < 3; j++)
    {
        fscanf(fp_pc, "%lf", &(vector[i][j]));
    }
}

/* read in base white Rg( $\lambda$ ) from R0 file */
fscanf(fp_stdR, "%d", &id_std);
if (id_std != 0)
{
    fprintf(fout, "data error in R0 file \n");
    exit();
}
for (i = 0; i < NW; i++)
{
    fscanf(fp_stdR, "%lf", &(base_white[i]));
}

/* Process all patches */
for (count = 1; count <= TOTAL_NB; count++)
{
    /* calculate Kx and R^ */
    fscanf(fp_conc, "%d%lf%lf%lf\n", &id_pred, &(cmy_conc[0]), &(cmy_conc[1]),
        &(cmy_conc[2]));

    fprintf(fp_rpred, "\n%d ", id_pred);
    for (i = 0; i < NW; i++)
    {
        k_sum = 0.0;
        for (j = 0; j < 3; j++)
        {
            k_sum = k_sum + vector[i][j] * cmy_conc[j];
        }

        r_pred[i] = base_white[i] * exp(-2.0 * k_sum); /* spectral model */
        fprintf(fp_rpred, "%0.6lf ", r_pred[i]);
    }
}

```

```

get_XYZ(r_pred, W, &tris_pred);
XYZ_Lab(tris_pred, white_ref, &lab_pred);

/* read in standard color's R() */
fscanf(fp_stdR, "%d\t", &id_std);
if ( id_std != id_pred)
{
    fprintf(fout,"data matching error in std and pred files \n");
    break;
}
for (i = 0; i < NW; i++)
{
    fscanf(fp_stdR, "%lf", &(r_std[i]));
}

get_XYZ(r_std, W, &tris_std);
XYZ_Lab(tris_std, white_ref, &lab_std);
Lab_LabLCh(lab_std, &lch_std);

dE[count] = sqrt( (lab_pred.L - lab_std.L) * (lab_pred.L - lab_std.L) +
                  (lab_pred.a - lab_std.a) * (lab_pred.a - lab_std.a) +
                  (lab_pred.b - lab_std.b) * (lab_pred.b - lab_std.b)
                );

dE_sum += dE[count];
if ( dE_max < dE[count] ) dE_max = dE[count];

fprintf(fout,"%d %.3f %.3f %.3f %d %.3f %.3f %.3f %.3f %.3f %.3f\n",
        id_pred, lab_pred.L, lab_pred.a, lab_pred.b,
        id_std, lab_std.L, lab_std.a, lab_std.b,
        lch_std.L, lch_std.C, lch_std.H, dE[count]);
}

dE_avg = dE_sum / (float) TOTAL_NB;
for ( count = 1; count <= TOTAL_NB; count++)
{
    sum_msq += (dE[count] - dE_avg) * (dE[count] - dE_avg) ;
}
dE_stdev = sqrt( sum_msq / (float) (TOTAL_NB - 1));

fprintf(fout,"Average dE %.3lf\n", dE_avg);
fprintf(fout,"Standard deviation %.3lf\n", dE_stdev);
fprintf(fout,"Max dE %.3lf\n", dE_max);

fclose(fp_stdR);
fclose(fp_pc);
fclose(fp_conc);
fclose(fp_d50);
fclose(fp_rpred);
fclose(fout);

```

Appendix E

Program to retrieve raw scanner digital counts

This program was used to interface with the D4000 drum scanner to get the raw red, green and blue scanner digital counts without any transformation. It was developed with the Howtek D4000 C language interface library version 2.06 for Macintosh with Think C 6.0 compiler. The actual code was build on top of the sample code included in the library. The intention here is to show what were added to make the library to work without disclosing the Howtek's source code. With a copy of the C interface library, one should be able to rebuild this complete program.

```
/*
    File:          Sample.c

    Contains:      A modified version of Apple's Sample.c that shows how to use the D4000
scanner.

    Written by:    Rick Roy

    Copyright:     Copyright © 1992 Howtek, Inc.
                  All Rights Reserved.

    Change History (most recent first):

        <31>      4/26/93      RAR      Mods for final SCSI toolkit w/IEC, etc.
        <30>      4/26/93      RAR      Mods for final SCSI toolkit w/IEC, etc.
        <29>      3/18/93      RAR      Final mods for release Toolkit w/CosMYK.
        .
        .
        .

    To Do:  resolution menu dimming.
*/

/*-----
#
#   Apple Macintosh Developer Technical Support
#
#   MultiFinder-Aware Simple Sample Application
#
#
```



```

#      Sample
#
#      Sample.c              C Source
#
#      Copyright © 1989 Apple Computer, Inc.
#      All rights reserved.
#
#      Versions:
.

#
#      1.04                      04/91   Updated for MPW 3.2
#
#
#      Sample is an example application that demonstrates how to
#      initialize the commonly used toolbox managers, operate
#      successfully under MultiFinder, handle desk accessories,
#      and create, grow, and zoom windows.
#
#      It does not by any means demonstrate all the techniques
#      you need for a large application. In particular, Sample
#      does not cover exception handling, multiple windows/documents,
#      sophisticated memory management, printing, or undo. All of
#      these are vital parts of a normal full-sized application.
#
#      This application is an example of the form of a Macintosh
#      application; it is NOT a template. It is NOT intended to be
#      used as a foundation for the next world-class, best-selling,
#      600K application. A stick figure drawing of the human body may
#      be a good example of the form for a painting, but that does not
#      mean it should be used as the basis for the next Mona Lisa.
#
#      We recommend that you review this program or TESample before
#      beginning a new application.
#
-----*/

/* Segmentation strategy:

This program consists of three segments. Main contains most of the code,
including the MPW libraries, and the main program. Initialize contains
code that is only used once, during startup, and can be unloaded after the
program starts. %A5Init is automatically created by the Linker to initialize
globals for the MPW libraries and is unloaded right away. */

.

.

/* add global variables for output */

```

```

FILE *fpo, *fpnext;

#pragma segment Main

main()
{
#ifdef THINK_C
    UnloadSeg((Ptr) _DataInit);          /* note that _DataInit must not be in Main! */
#endif

    /* filename add output variables */
    char *rgbfile = "rgb_500dpi.raw";
    char *rgbtext = "rgb_500dpi.text";
    fpo = fopen(rgbfile, "w");
    fpnext = fopen(rgbtext, "w");

    /* 1.01 - call to ForceEnvirons removed */

    /*      If you have stack requirements that differ from the default,
            then you could use SetApplLimit to increase StackSpace at
            this point, before calling MaxApplZone. */
    MaxApplZone();          /* expand the heap so code segments load at the top */

    Initialize();          /* initialize the program */
#ifdef THINK_C
    UnloadSeg((Ptr) Initialize);          /* note that Initialize must not be in Main! */
#endif
    SetProgStatus( eAllocMemory );

    EventLoop();          /* call the main event loop */

    /* close output file */
    (void) fclose(fpo);
    (void) fclose(fpnext);
}

void EventLoop() {
    const long    someSpace = 40000;
                  /* Absolute minimum slop that we can live with (found empirically) */

    /* pointer to output file - rgb pixel data */
    unsigned char *writePtr;
    short         *intPtr;
    short         pix_width;
    short         target_x;          /* needed target's image width of x = inch * dpi*/
    unsigned char *int8Ptr;
    short         *int12Ptr;
    .
    .
    .

    unsigned short nbytes;          /* Bytes per line of image data read in! */

```

```

long          bufSize;
long          lineNum;
long          waitTime, hSkipper, vSkipper;
Ptr          bufPtr;
Ptr          padbufPtr;      // rwe padding buffer
char          errorString[255];
short         whichPixel, screenBytesPerPixel, anInt;
short         count;         // rwe general loop counter
USM_DATA      usmBlock;
UCR_DATA      ucrBlock;
.
.
.

do {
    if ( NoErrorOrCancel() ) {
        waitTime = 60;
        Switch ( gProgStatus ) {

            case eAllocMemory:
                .
                .

                (**srcBitsH).baseAddr = padbufPtr;

#ifdef THINK_C
                GetWMgrPort( &theWMgrPort );
#else
                GetWMgrPort( &((GrafPtr) theWMgrPort) );
#endif

                SetCursor(&qd.arrow);
                SetProgStatus(eFindAScanner);
                break;

            case eFindAScanner:
                SetCursor( *GetCursor(watchCursor) );

                /* Here are the default parameters for our first scan. We are putting
them          in the scan control block because it is a convenient storage place. They
will          be used to set up the controls in the window so the user can adjust
them.         After we call d4_init_io(...), these values will be overwritten!
                */
                gSCB.lamp = TRANSMISSIVE;
                gSCB.collection = LINEAR_MODE;
                gSCB.color_channel = RED_GREEN_BLUE;
                gSCB.pixel_size = TWELVE_INV_BIT;
                .

```

```

        gSCB.pixel_size = EIGHT_BIT;

        gSCB.x_dpi = gSCB.y_dpi = gDesiredResolution;
        gSCB.focus_pos = CP_OVERRIDE;
        gSCB.async_flag = GPIB_A_SYNC;          / *          o r

GPIB_SYNC */

        .
        .
        .
        break;

case eGetParams1:
    /* Set all the things we want before displaying our controls. */

    .
    .
    break;

case eGetParams2:          /* Wait for user to set params and click "Continue".*/

    .
    .
    break;

case eInitIO:      /* Now we can contact the scanner (we only needed
                    gSCB.interface and scsi_id/gpib_device). */
    if (alreadyInitd) {
        SetProgStatus( eGetParams3 );
        break;
    }
    SetCursor( *GetCursor(watchCursor) );
    gErrorType = d4_init_io(&gSCB);

    /* debug */
    If ( gErrorType != noErr )
    {
        sprintf(errorString, "d4_init_io error = %d\n", gErrorType);
    }
    break;

case eGetParams3:          /* Now we're talking to the scanner; replace current
                            gSCB parameters w/ chosen ones. */

    /* this is the place to set the global variables, including all
       the options in the menu and the hard coded values!
       set resolution
       gSCB.x_dpi = gSCB.y_dpi = gDesiredResolution;
       */

    gSCB.x_dpi = 500;
    gSCB.y_dpi = 500;

```

```

gSCB.pixel_size = gDataSize;

if (gTransparency)
{
    gSCB.lamp = TRANSMISSIVE;
}
else
{
    gSCB.lamp = REFLECTIVE;
}

if (gLogModeScan)
{
    gSCB.collection = LOG_MODE;
}
else
{
    gSCB.collection = LINEAR_MODE;
}

switch (gColorsWanted) {
    case iRedOnly:
        gSCB.color_channel = RED_ONLY;
        break;
    case iGreenOnly:
        gSCB.color_channel = GREEN_ONLY;
        break;
    case iBlueOnly:
        gSCB.color_channel = BLUE_ONLY;
        break;
    default:
    case iRGBChannels:
        gSCB.color_channel = RED_GREEN_BLUE;
        break;
    case iCMYChannels:
        gSCB.color_channel = CMY_ONLY;
        break;
    case iCMYKChannels:
        gSCB.color_channel = CMYK_ONLY;
        break;
}

.
.

/* Calculate the scan window from gScanWindowCenter. */
CalculateSCBWindow();

/* define the scanning area and position */
gSCB.x_start = 1000; /* leave 1 inch space for taping the film */
gSCB.y_start = 1000; /* 1 inch for tape */

```

```

gSCB.x_length = 4000; /* x / 1000 = # inch */
gSCB.y_length = 5000; /* y/ 1000 = inch */

/* Calculate or specify the look up table. */
/* lut minmax, load the built LUT into &lutPtr */
CalculateLUTStuff(lutPtr, minVal, maxVal);
.
.
.

/* Note: someday we should have controls for the rest of these items. */
gSCB.xfer_format = PIXEL_PACKED; /* Not LINE_PACKED */
gSCB.aperture = ApertureFromDPI( );
HLock( (Handle) srcBitsH );
SetRect( &(*srcBitsH).bounds, 0, 0, kNiceImageWidth, 1 );
HUnlock( (Handle) srcBitsH );
break;

case eAutoFocusing:
.
.
.

case eSetParams:
    SetupUnSharpMasking(&usmBlock);
    SetupUnderColorRemoval(&ucrBlock);
.

#ifdef scannerConnected

    SetCursor( *GetCursor(watchCursor) );

    gErrorType = d4_setup_scan(&gSCB);

    if ( gErrorType != noErr )
    {
        sprintf(errorString, "d4setup error = %d\n", gErrorType);
    }
    .
    .
    .

    break;

case eInitScan:
.
.
    SetCursor( *GetCursor(watchCursor) );
    gErrorType = d4_scan(&gSCB);

#ifdef scannerConnected

```

```

/* debug */
if ( gErrorType != noErr )
{
    sprintf(errorString, "d4scan error = %d\n", gErrorType);
}
.
.
break;

case eAwaitData:
.
if ((gErrorType == INTERFACE_ERR) || (gErrorType == RT_ERR))
{
    /* Other errors here aren't fatal. */
    sprintf( errorString, "Waiting for scanner: %d\n", gErrorType);
    if (gErrorType == INTERFACE_ERR) {
        SetFatalError(errorString, gSCB.lib_error);
    } else {
        SetFatalError(errorString, gSCB.realtime_error);
    }
}
.
}
break;

case eScanLine:
    if ( lineNum > 0 ) {
        if (gInBackground)
            waitTime = 10; /* This will give the frontmost
                           application good performance at our expense. */
        else
            waitTime = 0; /* This will give us the best
                           scanning performance. */
        break;
    }
.
.
.
    /* io write the scanned binary data out to file */
    writePtr = (unsigned char *) bufPtr;

    if ( gSCB.pixel_size == EIGHT_BIT) /* need 8-bit data */
    {
        fwrite(writePtr, sizeof(unsigned char), nbytes, fpo);
        /* dpi * inches of size */
    }
    else
    {
        fwrite(writePtr, sizeof(short), nbytes / 2, fpo);
    }
}

```

```

        /* 12 bits = 2 bytes */
    }

    /* write output ascii number of the nbytes counts */
    if ( gSCB.pixel_size == EIGHT_BIT)
    {
        int8Ptr = (unsigned char *) bufPtr;
        for(pix_width = 0; pix_width < nbytes; pix_width++)
        {
            fprintf(fpText,"%d ", *int8Ptr++);
        }
    }
    else
    {
        int12Ptr = (short *) bufPtr;
        for(pix_width = 0; pix_width < nbytes/2;
            pix_width++)
        {
            fprintf(fpText,"%d ", *int12Ptr++);
        }
    }
    fprintf(fpText,"\n");

    If (!gScanBegan)
        gScanBegan = TickCount();
    readPending = false;
    waitTime = 0;    /* We've gotten a line of data, let's hurry
                       back in case there are more! */
    .
    .

}
break;

}
break;
}
} /*DoEvent*/

#pragma segment Initialize
void Initialize()
{

    /* 2 line added to solve compiler problem */
    Boolean TrapAvailable();
    Boolean GoGetRect();

} /* Initialize */

```


Appendix F

A Problem in the 12-bit Scanner Signal

A problem was discovered in the scanner system while scanning reflection target at 12-bit mode. It was noticed the 12-bit red, green and blue scanner digital counts were not linearly distributed according to the physical property of the target material. Hardware problem in the scanner was suspected to cause the distortion of the signal in certain signal range. However, this kind of problem was not found in the 8-bit scan. It was not found when scanning the transparent material in 12-bit mode since all the digital counts were under 3000.

One example is shown in the following figure where the gray patches of the Fuji IT8.7/2 target were scanned in 12-bit linear mode. The X-axis is the patch number of the gray patch from black to white. The Y-axis is the averaged scanner digital counts of the scanner output for each patch.

When the scanner signal is expected to be between 3200 and 3400, some unknown offset was introduced resulting a drop in the digital count of patch numbers 22, 23 and 24 as shown in the figure. This sudden drop in the output digital count not only makes a discrete curve in the scanner output but also makes it impossible to correct the problem since this drop is not a local offset, which is hard to model by the global offset term in the regression function. Thus, it was not possible to characterize the relation between the scanner digital counts and the material property under this circumstance.