

On-Line Color Camera Calibration

Elzbieta Marszalec and Matti Pietikäinen

Computer Vision Group, Department of Electrical Engineering, University of Oulu, Linnanmaa,
FIN-90570 Oulu, Finland

Abstract

This paper presents a practical approach to on-line color camera calibration under changing illumination conditions. Calibration is based on a color camera model and color constancy. In the first stage of the calibration a reconstruction of the current illuminant is performed based on an image taken from a scene with a calibrated color set. Using the updated power spectrum distribution of the current illumination the output camera values are corrected. Based on the corrected camera output values reconstruction of the reflectance spectrum of a random color object is performed and color features of the object can be determined under a required illuminant color temperature. The simulation experiments of the algorithm and results of tests on real images are discussed and the performance of the calibration is evaluated. The approach provides a real time color camera calibration procedure for many applications of machine vision.

1: Introduction

Color is an important characteristic of objects, and recently, it has been used more often in image analysis. A major problem with color machine vision is that the color images taken by various color sensors not only contain spectral properties of surfaces but also are greatly dependent on the intensity and spectral properties of illumination. This makes it difficult to obtain stable color features for object recognition and color measurements under real conditions where illumination is usually changing. Calibration is an important issue in the design of any kind of measurement system. A proper colorimetric calibration of the color camera system is needed in order to make color a practical tool in machine vision. A major problem for the calibration is that the illumination conditions are varying due to lamp aging, changes of driving current, switching of other light sources in the area of operation, changes in natural illumination, or due to various other unexpected reasons. On-line calibration of the camera system during operation of the machine vision system is often needed. The calibration methods proposed in the literature assume fixed and known illumination conditions during the camera system operation [1, 2, 3, 4], which is difficult to fulfil in many applications. The European Broadcasting Union (EBU) has recommended two equivalent measurement methods to assess the overall performance of color television cameras: the spectrophotometric method and the real samples method [1]. These methods were tested and evaluated by Dalton [2]. The former method

requires full spectral analysis of the camera from which reproduction of a set of test colors is computed, whereas the latter measures the actual camera reproduction when imaging a calibrated set of the test colors. These methods require *a priori* information of spectral radiance factors of calibrated color samples. Strachan has adopted the real sample method for calibration of a video digitizing system using the Macbeth color chart and white calibration box [3]. The accuracy of the methods discussed above is affected by the transformation of the camera's output into the CIE parameters, which usually is not very reliable as the spectral sensitivities of the camera are not linear transformations of the CIE color-matching functions [4, 5]. Lee has proposed a method for colorimetric calibration of a video digitizing system which allows to be obtained both accurate chromaticity data of an object and recovery of its spectral reflectance or transmittance using the Macbeth color chart as a reference [4]. The reconstructed spectrum is a very important characteristic of an object as it is an invariant property of the object and can be used for its identification. Having the spectral reflectance of an object, its chromaticity can be determined for the CIE standards or other color metrics. A major drawback of the procedures presented above is that they are valid only under fixed, determined and strictly controlled illumination. Applying them to varying illumination conditions, which is most often the case in real scenes, results in serious errors in obtained color images. Therefore, it is desirable to make the calibration independent of changing illumination. The goal of our research is to develop an on-line color camera calibration procedure which takes into account varying illumination conditions. The proposed on-line calibration procedure has two stages: reconstruction of power spectral distribution of current illumination based on image taken from the scene with calibrated color set and correction of camera's output and then, recovery of spectral reflectance of the imaged object. On-line information on current illumination is extremely important in real applications; it is a necessary requirement for accurate reconstruction of the reflectance spectrum of the object. It is also very useful for separating highlights from images before color correction, to analyze shape from highlights, and to control illumination in the scene. None of the calibration procedures reported earlier provide information about the lighting conditions during the camera operation. Conceptually, the proposed procedure is a significant improvement of the colorimetric calibration procedure developed for fixed illumination conditions by Lee [4], and incorporates the work on color constancy of several different authors [5-14].

2: Theoretical principles of color camera calibration

The camera measures a color signal which depends on illumination, spectral reflectances of observed objects, and the scene geometry. Output signal $I_{i(x,y)}$ of the i th camera channel (i =blue, green, red) is described by expression

$$I_{i(x,y)} = K \int_{\lambda_1}^{\lambda_2} S(\lambda) \rho(\lambda) \eta_i(\lambda) d\lambda \quad (1)$$

where K is a constant which takes into account the scene geometry, λ is the wavelength, λ_1 and λ_2 are lower and upper limits of integration, respectively, $S(\lambda)$ is the spectral power distribution of illumination, $\rho(\lambda)$ is the spectral reflectance of an object, and $\eta_i(\lambda)$ is the spectral sensitivity of the i th camera channel.

Spectral reflectance $\rho(\lambda)$ can be expressed as a sum of two parts: regular reflectance (or directional) $\rho_r(\lambda)$ and diffuse reflectance $\rho_d(\lambda)$ [15]

$$\rho(\lambda) = \rho_r(\lambda) + \rho_d(\lambda) \quad (2)$$

The regular reflectance possesses the information on surface structure properties and can be considered constant in visible spectrum for dielectric materials, while the diffuse reflectance carries information on the chromaticity of an object. So it is important for colorimetric calibration to use diffusing, flat reference color samples in order to avoid the effect of surface structure on camera calibration.

From formula (1) we can observe that changes of illumination cause changes in the output signal of the camera for the same observed color object. This introduces errors into the calibration procedure of the camera as well as into the algorithms which use camera outputs as a source of chromaticity information on the analysed scene. In order to solve the problem, invariant features from the color signal must be determined, i.e. the spectral characteristics of illumination and object reflectance. In computer vision the problem of recovery of the spectral characteristics of objects or illumination is formulated as color constancy.

For color constancy certain assumptions about the structure of the scene are used, mainly dealing with the properties of illuminants and surfaces. Most of the present color constancy algorithms assume that spectral reflectances of most natural objects and power distributions of most light sources vary smoothly with respect to wavelength. For their description finite-dimensional linear models are used [5-14, 16, 17]. For this reason the illuminant power distribution $S(\lambda)$ can be represented as a linear combination of a fixed set of basis functions $S_k(\lambda)$, and surface spectral reflectance $\rho(\lambda)$ can be represented as a linear combination of another set of basis functions $\rho_j(\lambda)$

$$S(\lambda) = \sum_{k=1}^p a_k S_k(\lambda) \quad \text{for } p=1, 2, 3, \dots, N \quad (3)$$

$$\rho(\lambda) = \sum_{j=1}^q b_j \rho_j(\lambda) \quad \text{for } q=1, 2, 3, \dots, N \quad (4)$$

where a_k , b_j are the characteristic parameters representing spectral properties of illumination and surface reflectance, respectively.

Approximating the integrals as summations over wavelength and taking into account the assumption mentioned above formula (1) can be rewritten in the form

$$I_{i(x,y)} = \sum_{k=1}^p a_k \sum_{\lambda=\lambda_1}^{\lambda=\lambda_2} S_k(\lambda) \rho(\lambda) \eta_i(\lambda) \quad (5)$$

when the spectral radiance $\rho(\lambda)$ is a *priori* known or as

$$I_{i(x,y)} = \sum_{j=1}^q b_j \sum_{\lambda=\lambda_1}^{\lambda=\lambda_2} S(\lambda) \rho_j(\lambda) \eta_i(\lambda) \quad (6)$$

when the illumination $S(\lambda)$ is given.

Equations (5) and (6) are used for reconstruction of unknown illumination and unknown reflectance, respectively. For this, the characteristic parameters a_k , and b_j must be calculated first from these equations, and then put into formulas (3) and (4), respectively. From equations (5) and (6) it can also be seen that when n different reflectances or illuminants are used, the $3n$ outputs of the camera are obtained. These equations can then be represented in a matrix form as

$$I = MV \quad (7)$$

where I is a vector formed from $3n$ outputs of the color camera; the dimension of the vector is $3n$. V is a vector of unknown characteristic parameters a_k or b_j with dimensions p or q , respectively. M is a matrix, which, in the case of illuminant reconstruction, is formed from the basis functions $S_k(\lambda)$, reflectance spectra of n different color objects $\rho_m(\lambda)$ ($m=1,2,\dots,n$), and the spectral sensitivities of color camera $\eta_i(\lambda)$; the dimension of the matrix is $(3n, p)$. In the case of spectral reflectance reconstruction M is formed from the basis functions $\rho_j(\lambda)$, spectral power distributions of n different illuminants $S_m(\lambda)$, and the spectral sensitivities of color camera $\eta_i(\lambda)$; the dimension of the matrix is $(3n, q)$.

Equation (7) is solved with standard routines of linear algebra. It is a basis for obtaining the characteristic parameters. As the camera has only three output channels, only three basis functions a_k or b_j can be determined by using one known reflectance or illuminant, respectively. In the case when more than one color sample or one illuminant is used, more coefficients a_k or b_j are available, and spectrum reconstruction can be performed with higher accuracy. If the number of camera outputs ($3n$) is at least twice the number of basis functions used (p or q), the solution of equation (7) is found by the least squares method, which additionally increases the accuracy of spectrum reconstruction.

Equation (7) is a core part of our proposed on-line color camera calibration method [18]. It allows us to obtain power spectral distribution of current illumination, which is used to correct the camera's output under this illumination. Then, the corrected signals are used for reconstructing the spectral reflectance of a color object. For reconstruction of the illumination, a reference set of calibrated color samples is used. A block diagram of the calibration system is presented in Figure 1. This is an on-line calibration procedure, because, the illuminant spectrum reconstruction, the camera output correction and the object's spectral reflectance reconstruction

tion are performed continuously during system operation. Depending on the application the color parameters of the object can be determined either in the CIE or in other color spaces.

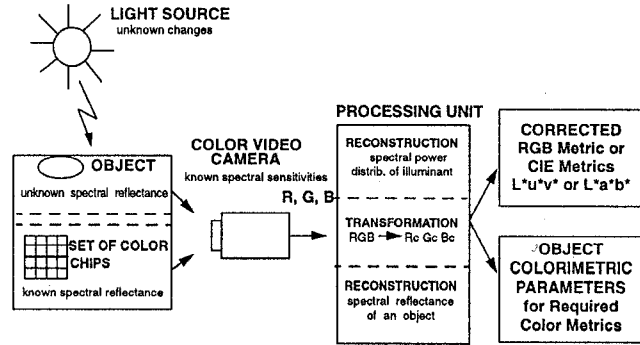


Figure 1. Block diagram of on-line calibration of a video camera digitizing system.

3: On-line color camera calibration procedure

We assume that the spectral sensitivities of the camera channels are *a priori* known and uniform over the image. Also, we assume spectral reflectances for a reference color set are given, illumination is uniform over the image, and color camera is operated with a fixed white balance. These assumptions are commonly used in colorimetric calibration of the vision systems [1-4] and color constancy algorithms [5-7, 11-14]. Spectral data of the camera and the color samples can be obtained from the manufacturers.

The calibration procedure has two stages: adjustment and on-line calibration. In the first, performed only once before on-line operation, the camera system is adjusted and prepared for image acquisition. The automatic gain control, the flare and contour correctors are switched off. The white balance is done manually and the camera's offset and gain are adjusted to ensure linearity of the output signals with no clipping or blooming. Next, an image of a reference set is taken for creating a gray-balanced scheme and obtaining the scaling factors between theoretical and real system's output. Then, the system's spectral transfer functions are determined by multiplying the spectral sensitivities of the camera by the scaling factors of each channel of the camera and in the further analysis $\eta_i(\lambda)$ stands for the system's spectral transfer functions. The obtained values are used in calculation of theoretical outputs of the system in the second part of the algorithm. In the second stage on-line calibration is realized, i.e. on-line correction of the output signals according to illumination variations, and recovering of the spectral reflectance of the color object. The second stage has the following steps:

STEP1: Matrix $M1$, with dimension $(3n, p)$, is obtained from the spectral data of the video digitizing system's transfer function, $\eta_i(\lambda)$, reflectance spectra of n reference colors, $\rho_m(\lambda)$, and basis functions of illuminant, $S_k(\lambda)$. The rk th ($r=1, 2, \dots, 3n$ and $k=1, 2, \dots, p$) entry of $M1$ is

$$\lambda = \lambda_2 \sum_{\lambda = \lambda_1} S_k(\lambda) \rho_m(\lambda) \eta_i(\lambda) \quad \text{where } m = 1, 2, \dots, n \quad (8)$$

Three-dimensional array $M2$ with dimension $(3, q, l)$, where l is the number of wavelengths, is formed from spectral data of system's transfer function, $\eta_i(\lambda)$, and basis functions of reflectance $\rho_j(\lambda)$. The ij th ($i=1, 2, \dots, 3, j=1, 2, \dots, q, f=1, 2, \dots, l$) entry of $M2$ is

$$\rho_j(\lambda) \eta_i(\lambda) \quad (9)$$

$M1$ and $M2$ are calculated only once at the beginning of this stage of the algorithm and stored in the memory.

STEP2: An image of the reference color set and the object is taken. Output signals are linearized and corrected according to the black and white levels [formulas (A1), Appendix I]. Three output signal values for each reference sample are put into vectors I_{ref} with dimension $(3n)$ and into matrix M_{ref} with dimension $(n, 3)$. Three output signal values for the object are placed into vector I_{obj} with dimension (3) . Vector I_{ref} and matrix $M1$ are used to calculate the characteristic parameters a_k of the current illumination from formula (7) using the least squares method. Spectral power distribution $S(\lambda)$ of the current illumination is obtained from formula (3) and normalized to the value $S(560)=100$. In the further analysis $S(\lambda)$ (vector S with dimension (l)) stands for the normalized values of spectral power distribution. The matrix $M3$ with dimension $(3, 3)$, for reconstruction of spectral reflectance of the object, is formed according to formula

$$M3 = M2S \quad (10)$$

STEP3: Using spectral reflectances of reference set, normalized power distribution $S(\lambda)$ and spectral system's transfer functions, the theoretical system output values are calculated [using formulas (1) and (A1), Appendix I] and stored in matrix M_{theor} with dimension $(n, 3)$.

STEP4: The theoretical and measured RGB values of the reference set are then used to obtain a correction matrix which transforms the RGB values to modified RGB. Based on the correction method described by Lee [4] the correction matrix $C(q, 3)$ is determined. Other correction methods, like the approaches described in [19, 20] can also be used.

STEP5: RGB values of the color object are interpolated in matrix M_{ref} and then the correction factors are determined from matrix C with the same interpolation scheme. RGB values of the object are modified by this correction.

STEP6: The corrected RGB values of the object and matrix $M3$ are used to obtain the characteristic parameters b_k from formula (7). Then the spectral reflectance of the object is calculated from formula (4).

STEP7: The chromaticity parameters of the object are determined for required color metrics (for required illuminant and color-matching functions or for the CIE standards) which can be specific for a given application.

During operation of the camera, STEP1, computationally most complex, is performed off-line only once after adjusting the system. Then simple procedures from STEP2 to STEP7 are performed very quickly (less than 1 second on a SUN-4) and continuously which guarantees on-line system calibration.

4: Simulated experiments

For simulation experiments the relative spectral sensitivities of a 3CCD Sony DXC-755P camera [21] and the spectral reflectance of Labsphere color samples [22], and of Macbeth ColorChecker chart [23] are used. The spectral characteristics of color samples are measured with a Minolta CM-2002 spectrophotometer adjusted to exclude the specular component. The Macbeth color chart includes 18 colored and 6 gray squares, and is used as a reference set whereas the Labsphere color samples, containing 8 pieces, simulate random objects. The camera RGB output values are calculated from formulas (1) and (A1), Appendix I, with lower and upper limits of 400 nm and 700 nm, respectively. The spectral power distributions of illuminants are obtained from the formulas and from tabulated data used in colorimetry [15]. The calibration procedure is tested for different types of illuminants at different correlated color temperatures. The daylight illuminant, typical for outdoor conditions, and xenon lamps are simulated with color temperatures ranging from 4000K to 20000K. For indoor conditions, typical for many industrial applications, the spectral data illuminants are calculated from the Planckian blackbody radiator formula, in the range of 2700K to 6000K. For illuminant reconstruction Judd's principal vectors [16] and polynomials are used as basis functions, whereas for objects - Cohen's principal vectors are applied [17]. Color differences are calculated in RGB and CIELUV color spaces.

To determine the overall goodness of fit of spectra reconstruction, the error δ_{rec} is calculated as the absolute values of differences between the original and the reconstructed spectral reflectances averaged over the wavelength band [24]. We can see from Table 1, that the daylight illumination is very well reconstructed by Judd's principal vectors, with an error of 0.0%, whereas the approximation by a polynomial function shows worse results giving the smallest error for 10th order. For indoor conditions the best reconstruction of the spectrum is achieved by a polynomial function. The 4th order is good enough and an approximation by higher polynomials does not improve the accuracy significantly. The highest error is obtained using the Judd's principal vectors for Planckian reconstruction. This is caused by using the principal vectors determined for recovery of spectra of daylight illumination with color temperature over 4000K, for lower color temperatures. The lower the color temperature the bigger the error. Results of simulation by a polynomial function are similar with those reported in [13, 14]. The examples of illuminant spectra reconstruction by Judd's vectors and 4th order of polynomial for Planckian illuminator and daylight illuminant are presented in Figures 2a and 2b, respectively.

Table 1. The average percent error for recovered illuminant.

Illumination	Temperature [K]	Judd's vectors	Polyn. 4th order	Polyn. 10th order
Daylight	4000-20000	0.0	1.8 - 2.3	1.2 - 1.7
Planckian	2400 - 6000	4.3 - 6.9	0.1 - 0.2	0.0

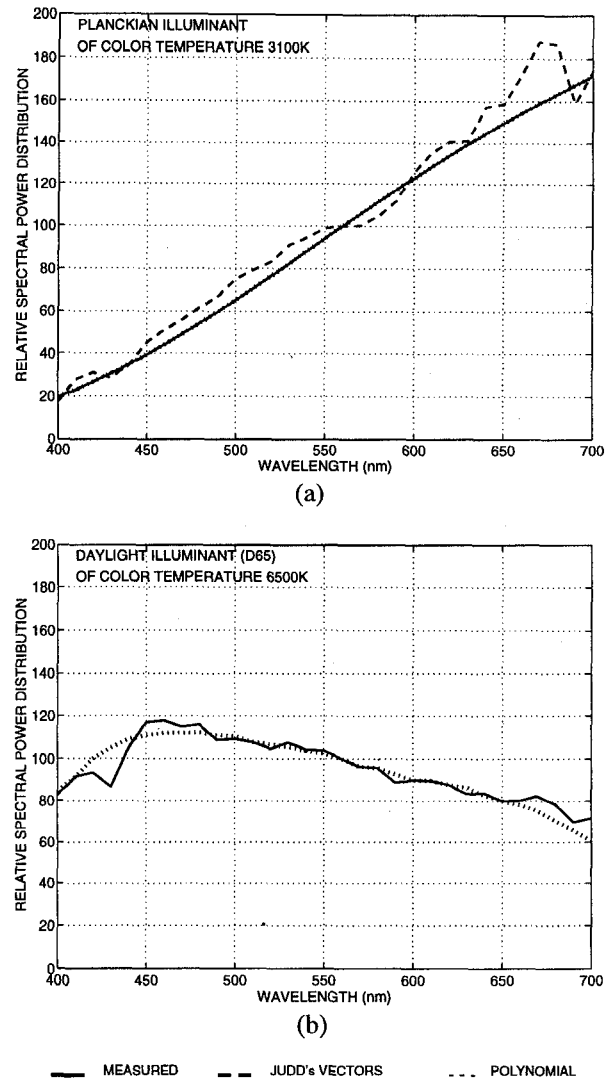


Figure 2. Simulation results for reconstruction of spectral power distribution: (a) Planckian illuminant of color temperature 3100K; curves for measured and polynomial values overlap; (b) daylight illumination of color temperature 6500K; curves for measured and Judd vectors values overlap.

The reconstruction of spectral reflectances of Macbeth and Labsphere samples with Cohen principal vectors for both types of illumination gives comparable results, with average error rates 4.2% for Macbeth, 7.1% for Labsphere and 5.2% for all samples of the two color sets.

In order to evaluate the performance of the calibration procedure we determine errors in the on-line calibration (OLC) and compare them with the errors from the calibration procedure under fixed illumination (FIC) applied for varying illumination conditions. The FIC calibration is performed for color temperature of illuminant T_F when the real illumination has changed and has color temperature T_V . In such a case camera output signals are generated for the illu-

minant of color temperature T_V , and their theoretical values for the temperature T_F (as done in STEP3). In the on-line calibration, both camera output signal values and their theoretical values are for the same illumination, i.e. color temperature T_V . Applying both calibration procedures to each color sample from the set, errors of spectrum reconstruction δ_{rec} , color difference in RGB color space ΔE_{RGB} , and color difference in CIELUV color space ΔE_{uv} [1] are determined, and then their average values for the set of samples is calculated. ΔE_{RGB} calculated as percentage error of the distance between two points in 3-dimensional Euclidean space.

In simulation two cases with OLC and FIC procedures for all Macbeth and Labsphere samples have been studied. In the first case FIC procedure is executed for Planckian illuminator of color temperature $T_F=2900K$ while current illumination T_V varies from 2900K to 6500K. In the second case the FIC procedure is performed for daylight conditions with color temperature 5500K and current illumination changes in the same range as in the previous case. For reconstruction of spectral power distribution of Planckian, the polynomial of 4th order is used. While for reconstruction of spectral power distribution of daylight illumination, Judd vectors are applied. Results of simulation for both cases are similar - the color differences and error of spectrum reconstruction for the FIC procedure in changing illumination conditions are higher than for the OLC procedure (Table 2, for the first case - $T_F=2900K$). It means that even slight

Table 2. The average color differences for FIC (for Planckian of 2900K) and OLC

Illuminant	T_V	FIC Planckian $T_F=2900$			OLC T_V		
	K	δ_{recavg}	ΔE_{RGBavg}	ΔE_{uvavg}	δ_{recavg}	ΔE_{RGBavg}	ΔE_{uvavg}
Planckian	2900	5.10	4.3	6.2	5.10	4.3	6.2
	3100	5.72	6.8	7.0	5.12	4.1	6.1
	3400	9.83	9.4	13.5	5.13	4.2	5.9
Daylight	5000	34.72	17.3	28.3	5.16	3.9	5.6
	5500	39.50	23.9	34.0	5.20	3.9	5.5
	6500	44.30	35.9	38.80	5.22	3.7	5.5

changes in color of light seriously affect the accuracy of the calibration method developed for fixed illumination conditions. The higher the difference between temperatures T_F and T_V the bigger the chromaticity error. The accuracy of the on-line procedure OLC is almost stable for varying color temperature of illumination and better than the accuracy of the calibration method constrained to have a fixed illumination. When color temperature of the illuminant is unchanged (e.g. $T_V=T_F$) both calibration procedures provide the same results. An example of spectrum reconstruction of a yellow Labsphere sample applying OLC and FIC procedures for $T_F=2900K$ and $T_{V1}=3100K$ and $T_{V2}=3400K$ is shown in Figure 3. As can be noticed the curves of reconstructed

reflectance spectra of the object obtained for OLC procedure under mentioned above color temperatures T_{V1} and T_{V2} overlap. Whereas the curves delivered by FIC differ and present worse results of reconstruction.

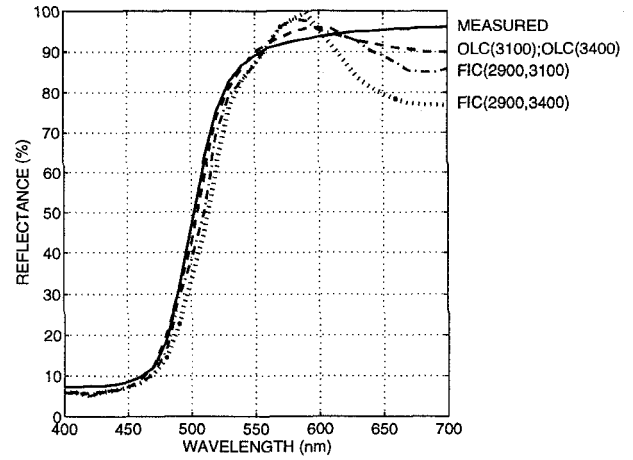


Figure 3. Simulation results for reconstruction of spectral reflectance of a yellow Labsphere sample obtained with OLC and FIC procedures for $T_F=2900K$ and $T_{V1}=3100K$ and $T_{V2}=3400K$; curves for OLC(3100) and OLC(3400) overlap.

5: Tests with real images

For verification of the results experimental tests with a video digitizing system were performed in a dark room. The video digitizing system included a 3CCD Sony DXC-755P camera and a true color digitizer (Data Cube). Four symmetrically located halogen lamps were used to provide uniform illumination of the captured scene. The color temperature of illumination was changed within the range 2800K to 3400K by changing voltage in the power supply. The color temperature of each halogen lamp was determined using a Minolta colormeter. Uniformity of color temperature over the scene was checked by measurements in a number of points. Halogen lamps were the only source of light in the dark room during the experiments. Temperature conditions in the room were kept stable. The reference Macbeth chart and all Labsphere color samples were placed close together to be seen in the same image. Each time when an image was taken the color temperature of illumination was measured by the colormeter. For each image the spectral power distribution of illumination obtained from the calibration algorithm was compared with the theoretical value calculated from the Planckian blackbody formula for the measured temperature. Color temperature of illuminant was changed by 50K and the whole procedure was repeated. Comparing the reconstruction results of the power spectrum distribution of the illuminant with the values obtained by simulation, an error of 1.5% is obtained for color temperatures T_V from 2900K to 3400K which is considered good for real conditions. Error values in the experiments are higher than for the simulation due to differences in spectral transfer functions of the video digitizing system and spectral sensitivities of the cam-

era, and quantisation and computational errors. For all color samples average error values δ_{recavg} , ΔE_{RGBavg} , ΔE_{uvavg} are calculated for both calibration procedures, FIC for $T_F=2900K$ and OLC, when color temperature of illumination T_V changes as stated above. Results of error calculations are collected in Table 3. In both cases of simulation and experimental tests the error of spectrum reconstruction for illuminant is lower then for the object. It is that the recovery of power spectrum distribution of illuminant is obtained from a larger number of camera outputs ($3n$, where n is the number of reference color samples) than in the case of the object (3 outputs).

Table 3. The average color differences for FIC (for Planckian of 2900K) and OLC in tests with real images.

Illuminant	T_V	FIC Planckian $T_F=2900K$			OLC T_V		
		δ_{recavg}	ΔE_{RGBavg}	ΔE_{uvavg}	δ_{recavg}	ΔE_{RGBavg}	ΔE_{uvavg}
Planckian	2900	7.7	7.3	9.3	7.7	7.3	9.3
	3100	11.2	10.9	12.2	8.2	7.6	9.1
	3400	16.2	15.2	16.1	8.1	7.2	8.9

We can also see, as in the case of simulation, that the FIC procedure generates higher chromaticity errors than OLC procedure for the same varying illumination. Errors obtained for both calibration procedures in tests with real images are higher than those obtained in the simulation due to the same reasons as in the reconstruction of power spectrum distribution of illuminant. Experimental tests have proved that the on-line calibration procedure proposed in this paper is much more appropriate for color camera calibration in varying illumination conditions than the procedures based on the assumption of fixed illuminant.

The described calibration procedure is a significant improvement over the one developed for fixed illumination and performs well under real conditions. Further research will be directed towards improving the accuracy of reflectance spectrum reconstruction, and correction of camera's output in cases of color objects with more complex texture and shape.

6: Conclusions

An approach to on-line color camera calibration based on color camera model and color constancy was presented. The proposed method allows on-line reconstruction spectra to be obtained for both the illuminant and the color object, which are invariant features of color signal entering the camera. The method performed very well in simulation tests and in experiments with real image data. The procedure is fast, more accurate and universal than earlier colorimetric calibration methods developed for fixed illumination conditions and more suitable for real illumination conditions. Thus the presented calibration method should increase the usefulness of color cameras in many practical applications.

References

1. European Broadcasting Union. Methods of measurement of the colorimetric fidelity of television cameras. Measurement procedures. Supplement 1 to Tech. 3237-E. 1989 (second edition).
2. C. J. Dalton. The measurement of the colorimetric fidelity of television cameras. *Journal of the Institution of Electronic and Radio Engineers*, 58: 181-186, 1988.
3. N. J. C. Strachan, P. Nesvadba and A. R. Allen. Calibration of a video camera digitizing system in the CIE $L^*u^*v^*$ colour space. *Pattern Recognition Letters*, 11: 771-777, 1990.
4. R. L. Lee, Jr. Colorimetric calibration of a video digitizing system: algorithm and applications. *COLOR Research and Applications*, 13: 180-186, 1988.
5. L. T. Maloney. Computational approaches to color constancy. *Applied Psychology Laboratory*. Technical Report 1985-01, Stanford University, January, 1985.
6. G. West and M. H. Brill. Necessary and sufficient conditions for von Kries chromatic adaptation to give color constancy. *J. Math. Biol.*, 15, 249-258, 1982.
7. J. A. Worthey. Limitations of color constancy. *J. Opt. Soc. Amer.* A2, 7, 1014-1026, 1985.
8. J. A. Worthey and M. H. Brill. Heuristic analysis of von Kries color constancy. *J. Opt. Soc. Amer.* A3, 10, 1708-1712, 1986.
9. L. Maloney and B. Wandell. Color Constancy: a method for recovering surface spectral reflectance. *J. Opt. Soc. Am.* A1, 3: 29-33, 1986.
10. B. A. Wandell. Color rendering of color camera. *Color Research and Application*. 11(Supplement 1986): S30-S33, 1986.
11. R. Bajcsy, S. W. Lee and A. Leonardis. Color image segmentation and color constancy. *Perceiving, Measuring, and Using Color*. Proc. of SPIE, 1250: 245-253, 1990.
12. D. A. Forsyth. A novel algorithm for color constancy. *Intern. J. Comput. Vision*, 5, 1: 5-35, 1990.
13. M. Abe, H. Ikeda, Y. Higaki and M. Nakamichi. A method to estimate Correlated Color temperatures of illuminants using a color video camera. *IEEE Transaction on Instrumentation and Measurement*, 40: 28-33, 1991.
14. C. L. Novak and S. A. Shafer. Supervised color constancy for machine vision. *Physics-Based Vision*. Color. Jones and Bartlett, 284-299, 1992.
15. G. Wyszecki and W. S. Stiles. *Color Science: Concepts and Methods, Quantitative Data and Formulae*. 2nd ed., John Wiley, New York, 1982.
16. D. B. Judd, D. L. McAdam, and G. Wyszecki. Spectral distribution of the typical daylight as a function correlated color temperature. *J. Opt. Soc. Am.*, 68, 437-450, 1978.
17. J. B. Cohen. Dependency of the spectral reflectance curves of the Munsell color chips. *Psychonomic Science*, 1, 369-370, 1964.
18. E. Marszalec. *Color camera modeling and calibration*. Technical Report. Computer Vision Group, University of Oulu, 1993.
19. J. Shiao and L. C. Williams. Semiautomatic printer calibration with scanners. *J. of Imag. Sc. and Technology*, 36: 211-219, 1992.
20. H. R. Kang. Color scanner calibration. *J. of Imag. Sc. and Technology*, 36: 162-170, 1992.
21. Sony CCD-755P. *Service Manual*. Sony Corporation.
22. Labsphere. *Reflectance calibration standards*. 1988.
23. Macbeth ColorChecker. *Trademark product*. 1990.
24. J. P. S. Parkkinen, J. Hallikainen, T. Jääskeläinen. Characteristic spectra of Munsell colors. *J. Opt. Soc. Am.* A.6: 318-322, 1986.

Appendix I.

The linearized red, green and blue $R(A_n)$, $G(A_n)$, $B(A_n)$ values of each of the n color samples are corrected according to the black and white levels, using the following equations [3]:

$$X_n = \frac{X(A_n) - X(b)}{X(w) - X(b)} 100\% \quad (A1)$$

where $X = R, G, B$, and $X(b)$ and $X(w)$ are the black levels and the white levels of each camera channel, respectively. For calculations of the theoretical values of the camera output, the same formulas are used with the black levels equal zero.