Color Classification of Archaeological Fragments *

Martin Kampel and Robert Sablatnig
Vienna University of Technology
Institute for Computer Aided Automation
Pattern Recognition and Image Processing Group
Favoritenstr.9/183-2, A-1040 Vienna, Austria
{kampel,sab}@prip.tuwien.ac.at

Abstract

We are developing an automated classification and reconstruction system for archaeological fragments. The goal is to relate different fragments belonging to the same vessel based on shape, material and color, thus the color information is important in the pre-classification process. In this work a color specification technique is proposed, which exploits the fact that the spectral reflectance of materials like archaeological fragments vary slowly in the visible. We explain how the acquisition system is calibrated in order to get accurate colorimetric information with respect to archaeological requirements. Experimental results are presented for archaeological objects and for a set of test color patches.

1 Introduction

Ceramics are one of the most widespread archaeological finds and are a short-lived material. This property helps researchers to document changes of style and ornaments. Especially ceramic vessels, where shape and decoration are exposed to constantly changing fashion, not only allow a basis for dating the archaeological strata, but also provide evidence of local production and trade relations of a community as well as the consumer behavior of the local population. The purpose of ceramic classification is to get a systematic view of the material found [2, 6] and is used to relate a fragment to existing parts in the archive.

Archaeologists determine the specific color of a fragment by matching it to the Munsell color patches [7]. Since this process is done "manually" by different archaeologists and under varying light conditions, results differ from each other. Archaeologists need digital color images of fragments for archivation purposes, thus the color information which is normally achieved with a color measurement instrument can be gained directly from the digital image for each pixel in the entire image.

We propose a solution to the color classification assuming that the spectral reflectance of archaeological fragments varies slowly in the visible spectrum. We present an approach for accurate colorimetric information on fragments, performed on digital images containing archaeological fragments under different illuminants. A characteristic vector analysis [9] of the reference reflectance leads to an algorithm that computes the colorimetrically accurate reflectance out of a video digitizing system.

The paper is organized as follows: In Section 2 we describe the theoretical background, in Section 3 we explain how we specify the colorimetric variables in order to calibrate the acquisition system with respect to archaeological requirements. Experimental results are described in Section 4 and we conclude with a summary and outline the future work.

2. Theory and Notation

Much of human color-vision research focuses on color constancy since it is the perceptual ability that permits us to discount spectral variation in the ambient light and assign stable colors: Maloney and Wandell [4] considered that both lighting and spectral reflectance are unknown, whereas Lee [3] simplified that problem by assuming that spectral illumination is known. Color and reflectance based object recognition was presented by [1, 8]. In order to provide a device-independent color specification we use reference colors from the MacBeth Color chart [5].

Our approach rests upon Lee's method assuming that spectral illumination is known and that the spectral re-

*This work was supported in part by the Austrian Science Foundation (FWF) under grant P13385-INF.

flectance of our material varies slowly in the visible spectrum. This means that small changes of RGB values should lead to small changes in reflectance. Prior knowledge about the illuminant leads to chromaticity and luminance information.

Each RGB pixel in a digitized image has a value proportional to weighted integral over the visible spectrum. This integral depends on three spectral variables. These are the *spectral irradiance* $E(\lambda)$, which describes the energy per second at each wavelength λ. The proportion of light of wavelenght λ reflected from an object is determined by the *surface spectral reflectance* $S(\lambda)$. We assume that there are k distinct channels in the digitizing system, we use $k = 3'$ for red, green and blue. We denote the *spectral response* of the kth channel as $R_k(\lambda)$ and a pixel value for the kth color channel as p_k.

$$p_k = \int S(\lambda)E(\lambda)R_k(\lambda)d(\lambda) \tag{1}$$

Eq 1 describes the relationship between pixel values and spectral quantities. We approximate the three integrals above as summations over wavelength, using values every $10nm$ in the visible spectrum from $400nm$ to $700nm$. If the proportionality factor in the $R_k(\lambda)$ is subsumed, one can construct the following matrix equation (Eq. 2). m denotes the steps to be taken in the spectrum.

$$p = SER \tag{2}$$

$p \ldots$ 1 by 3 row vector (RGB pixel)
$S \ldots$ 1 by m row vector,(surface reflectance)
$E \ldots m$ by m diagonal matrix, (spectral irradiance)
$R \ldots m$ by 3 matrix, (system spectral transfer function)

If we know elements of two of the arrays on the right side of Eq. 2 and the corresponding RGB pixel values on the left side, we can solve the unknown array. Since only an approximated knowledge of the system function R is assumed, the goal will be to:

- specify the system transfer function R more accurately by analyzing color samples with known reflectance of the MacBeth Color patches.
- use this new information to find the unknown spectral reflectance of other samples illuminated by the same light source.

The goal of the first step is to improve the transfer function R which leads to R_{new} (Eq. 3).

$$R_{new} = RR_1 \tag{3}$$

Therefore we digitize an image of the color chart, which is illuminated by the same light source that will be used when we evaluate unknown color samples. The digitization gives a q by 3-matrix P containing RGB values, where q denotes the number of patches of the color checker. Since we know the illumination E and the set of q reflectances S, we can form the q-by-3 matrix SER_{new}. This leads to Eq. 4. For the unknown R_1 a least square solution is used, which leads to an improved estimate of the system's spectral transfer function.

$$P = SERR_1 \tag{4}$$

The goal of the second step is to calculate the reflectances of unknown color samples. We use the RGB-values from the digitized color samples p, the improved transfer function R_{new} and the spectral irradience E in order to calculate spectral reflectances S (See Eq. 2).

Since $S(\lambda)$ varies smoothly for fragments we can accurately represent the spectral reflectance of a set of color standards with the first few components of a characteristic vector analysis [9]. In effect, this analysis allows us to reduce the dimensionality of S and leads to an algorithm that gives colorimetrically accurate spectral reflectance from red-green-blue output of the video digitizing system.

S_{mean} is defined as mean vector (1 by m) from the color checker reflectances at $m = 30$ equally-spaced wavelengths across the spectrum. S_{basis} (n by m matrix) denotes the characteristic vectors used. We use $n = 3$ characteristic vectors to represent the original data. A 1-by-n vector of basis weights (denoted B) is calculated when solving Eq. 5 by inserting the digitized RGB values into p.

$$B = (p - S_{mean}ER)(S_{basis}ER)^{-1} \tag{5}$$

When we multiply S_{basis} by the appropriate vector B and add the result to S_{mean}, we can reconstruct any spectral reflectance S in our set of colors (Eq. 6). For a more detailed description of the algorithm see [3].

$$S = S_{mean} + BS_{basis} \tag{6}$$

The technique used is a method for examining a number of sets of multivariate response data and determining linear transformations of the data to a smaller number of parameters which contains essentially all the information in the original data.

3 Color estimation process

First, the three spectral variables - irradiance of the lightsource $E(\lambda)$, camera transfer function $R_k(\lambda)$ and reflectance $S(\lambda)$ of the MacBeth reference chart - have to be initialized.

We use Tungsten Halogen Floodlamps 7700 (150W) and TL-light as lightsources. In order to recover colorimetric data from our samples under a variety of lightsources we use different types of lightsources. The spectral distribution was given by the manufacturer. Figure 1 shows the typical spectral distribution of TL-82 and TL-95 with slight differences between these two lamps.

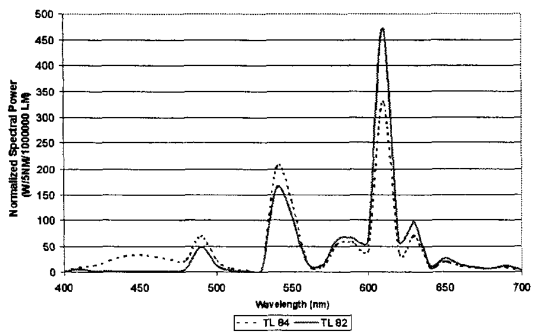

Figure 1. Spectral irradiance of TL-82 and TL-95

The video cameras used are a 3CCD DONPISHA XC-003P and a CCD-IKEGAMY ICD-700P. The Ikegamy camera is a single CCD-color CCTV camera, which is used to give out Y/C (chrominance/ luminance) separation signals. The Sony camera is a color video module, which uses a CCD for the pick-up device. It has an RGB signal output. Both cameras are one-chip-cameras. Figure 2 shows the spectral response curve of the DONPISHA camera. The data was provided by the manufacturer.

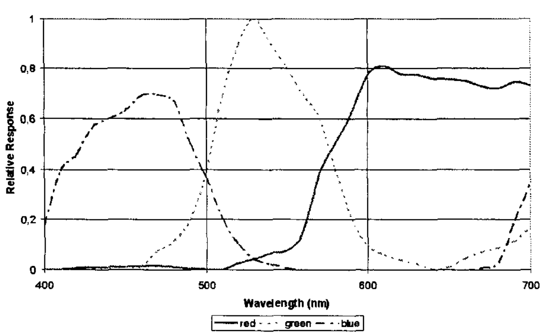

Figure 2. Typical spectral response of a Sony-camera

The spectral reflectance is scaled in equally-spaced wavelengths (every 10nm) across the spectrum. 12 colors of the MacBeth Color checker are used as a reference set and 12 are used for evaluation purposes. Their reflectance is measured using a spectroradiometer. For our reference set we choose colors which have a similar spectral distribution to the colors of our archaeological findings in order to maximize the achievable accuracy of the vector analysis.

In the next step we grab an image of an archaeological fragment, which leads to RGB values. Test regions are specified manually, and their RGB-Values are used to reconstruct the reflectance. Figure 3 shows two different test regions A and B.

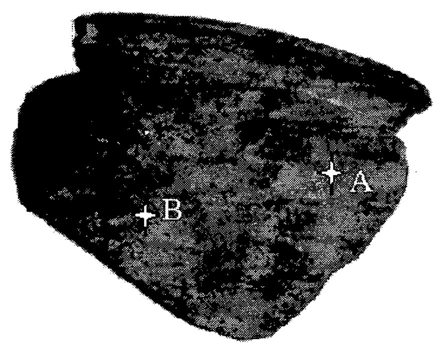

Figure 3. Test regions A and B

4 Results

Two experiments are presented: the first example with MacBeth Colors and the second with real fragments. In a first experiment we use the measured reflectance of 12 MacBeth color patches as reference and try to estimate the reflectance of the other 12 patches using the reference set. The resulting reflectance is compared to previous measured values.

Figure 4 shows the result for patch 1 (dark skin). In that case, the correlation equals $0,98$. The computed reflectances of the other 11 patches correlated between and $0,85$ and $0,98$ to their corresponding measured reflectances with an average correlation of $0,92$ (see Table 1). Lower correlation may be caused by the purely statistical representation of the underlying variables by the characteristic vector analysis.

In the second experiment we grab an image of a fragment and specify two test regions A and B (Figure 3). The reference set was chosen from the MacBeth color checker. The spectral reflectances of A and B are computed and visualized in Figure 5. For evaluation purposes we calculate CIE tristimulus values using a linear transformation and compare the achieved values with measured cromaticity coor-

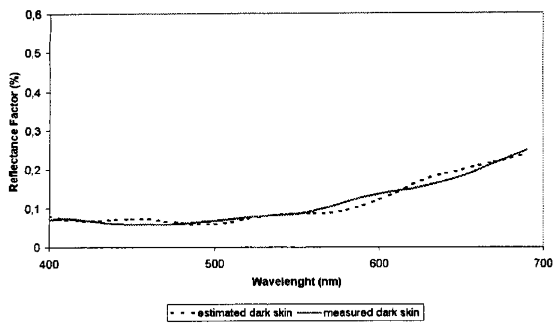

Figure 4. Measured and estimated spectral reflectance of a MacBeth Color Patch

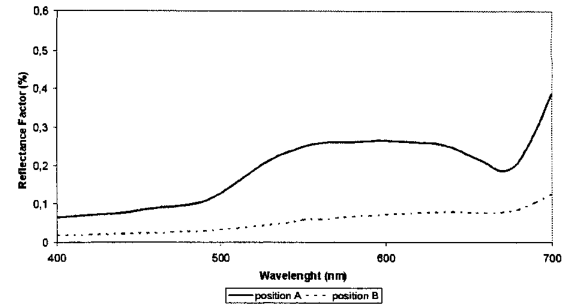

Figure 5. Calculated spectral reflectance of positions A and B

patchnr	corr	patchnr	corr
1	0.98	7	0.97
2	0.97	8	0.95
3	0.93	9	0.96
4	0.98	10	0.91
5	0.86	11	0.85
6	0.92	12	0.89

Table 1. Correlation between measured and calculated spectral reflectances of 12 Macbeth ColorChecker patches

dinates from a Chroma Meter CR-200b. Table 2 shows a comparison between measured and computed chromaticity coordinates. The final results are in the close neighborhood of the measured values. Since these results are influenced by the linear transformation we plan measurements using a spectroradiometer in order to allow direct comparison between measured and computed reflectances.

	Comp. A	Meas. A	Comp. B	Meas.B
x	0.48	0.33	0.49	0.40
y	0.39	0.34	0.41	0.37
Y	17.9	11.1	32.3	21.0

Table 2. Measured and computed cromaticity coordinates

5 Conclusion and Outlook

In this work we presented a technique for accurate color estimation, which plays an important role in the classification process for archaeological fragments. We proposed an application using a straightforward approach based on a linear color calibration technique. Since the color specification of a fragment is gained by different archaeologists and under varying lightning conditions the results differ from each other. The results obtained give a good initial estimate to the archaeologists. Future work goes towards color calibration without known illuminants in order to allow color estimation outside laboratory conditions.

References

[1] T. Gevers and W. M. Smeulders. Color-based Object Recognition. *Pattern Recognition*, 32(2):453–464, 1999.

[2] M. Kampel and R. Sablatnig. On 3d Modelling of Archaeological Sherds. In *Proc. of Int. Workshop on Synthetic-Natural Hybrid Coding and Three Dimensional Imaging*, pages 95–98, 1999.

[3] R. L. Lee. Colormetric calibration of a Video Digitizing System. *Colour Research and Application*, 13(3):180–186, 1988.

[4] L. T. Maloney and B. A. Wandell. Colour Constancy: a method for recovering surface spectral reflectance. *Journal of the Optical Society of America*, 3(1):29–33, 1986.

[5] C. S. McCamy, H. Marcus, and J. G. Davidson. A Colour-Rendition Chart. *Journal of Applied Photographic Engineering*, 2(3):95–99, 1976.

[6] C. Menard and R. Sablatnig. Computer based Acqusition of Archaeological Finds: The First Step towards Automatic Classification. In H. Kamermans and K. Fennema, editors, *Interfacing the Past, Computer Applications and Quantitative Methods in Archaeology*, number 28, pages 413–424, Leiden, March 1996. Analecta Praehistorica Leidensia.

[7] C. Menard and I. Tastl. Automated Color Determination for Archaeological Objects. In *Is&T 4th Color Imaging Conference*, pages 160–163, 1996.

[8] S. Nayar and R. Bolle. Reflectance Based Object Recogntion. *Int. Journal of Computer Vision*, 17(3):219–240, 1996.

[9] J. L. Simonds. Application of characteristic vector analysis to photographic and optical response data. *Journal of the Optical Society of America*, 53:968–974, 1963.