

# COLOR CLASSIFICATION OF CERAMICS USING SPECTRAL REFLECTANCE

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## ABSTRACT

*Every archaeological excavation must deal with a vast number of ceramic fragments. The documentation, administration and scientific processing of these fragments represent a temporal, personnel, and financial problem. 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 varies 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. Therefore, ceramics are used to distinguish between chronological and ethnic groups. Furthermore ceramics are used in the economic history to show trading routes and cultural relationships. 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 [10].

In order to make a later classification possible, the object is described in different ways: shape, decoration, technological manufacturing stage, material, and color. Shape is usually described in terms of type-series using traditional pottery classification systems. For this, the description of the profile is important. Decoration, material, color, and a careful examination of the traces left on the vessel which indicate the steps taken during the manufacturing process is a further important property to be investigated in order to perform a subsequent classification.

All descriptions of the object serve only one final aim: the correct *classification* of the material. When dealing with a collection of different objects it is natural to group similar items together, and separate them from the groups from which they differ. Pottery was made in a very wide range of forms and shapes. There are several different ways of classifying vessels: based on their shape, rim form, the presence of handles or spouts, decorative motifs and so on.

The purpose of classification is to get a systematic view of the material found (if every piece would be treated as unique, this would immediately lead to the wood-for-the-trees syndrome due to the vast amount of information), to recognize types, and to add labels for additional information as a measure of quantity. It is used to relate a fragment to existing parts in the archive. The color information is very important in the pre-classification process since archaeologists use this color information to relate a fragment to an excavation layer, age, manufacture, or even to a certain pot. The classification of fragments can be divided into two main parts: shape features and properties. The *classification of shape* defines the process where archaeologists distinguish between various features, like the profile [3], the dimensions of the object, like diameter, and the type of surface [7], whereas the *classification of material* copes with different characteristics of a fragment like the clay, the color [8] and the surface properties.

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Archaeologists determine the specific color of a fragment by matching it to the Munsell color patches [8, 12]. Since this process is done "manually" by different archaeologists and under varying light conditions, the results differ from each other. In general, photos of fragments are taken in order to have color representations in the archive. Due to different camera characteristics and changing light conditions the color of a fragment in images varies.

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. In practice, these advantages are offset by the difficulty of reliably translating the video camera's output into colorimetric variables.

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 with a priori known spectral illumination. A characteristic vector analysis [11] 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 sensor model used, 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. THE SENSOR MODEL

In order to perform accurate colorimetric information using video devices many approaches can be found in literature. 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 [5] considered that both lighting and spectral reflectance are unknown, whereas Lee [4] simplified that problem by assuming that spectral illumination is known. Color and reflectance based object recognition was presented by [1, 2, 9].

In order to provide a device-independent color specification we use reference colors from the MacBeth Color chart [6]. The color checker is a checkerboard array of 24 scientifically prepared colored squares in a wide range of colors. It is designed to help to determine the true color balance or optical density of any color rendition system. Each 13/4" color

square represents a natural object like human skin, foliage, and blue sky. They reflect light the same way in all parts of the visible spectrum. The MacBeth Color checker patches are representative samples for common reflectance characteristics. Figure 1 shows a fragment together with parts of the MacBeth rendition chart.



Figure 1: Archaeological fragment together with MacBeth color checker

The choice of the color checker or any other statistical sample drawn from the population of color standards clearly imposes a bias on the characteristic vector analysis. If the resulting basis vectors ultimately yield spectral reflectance that are colorimetrically accurate over a wide range of chromaticities, the color checker will be satisfactory for these purposes.

Our approach rests upon Lee's method assuming that spectral illumination is known and that the spectral reflectance 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. This is the *spectral irradiance*  $E(\lambda)$ , which describes the energy per second at each wavelength  $\lambda$ . The proportion of light of wavelength  $\lambda$  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 and use  $k = 3'$  for red, green and blue. We denote the *spectral response* of the  $k$ th channel as  $R_k(\lambda)$  and a pixel value for the  $k$ th color channel as  $p_k$ .

$$p_k = \int S(\lambda)E(\lambda)R_k(\lambda)d(\lambda) \quad (1)$$

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.

$$p = SER \quad (2)$$

$p \dots 1$  by 3 row vector (RGB pixel)  
 $S \dots 1$  by  $m$  row vector, (surface reflectance)  
 $E \dots m$  by  $m$  diagonal matrix, (spectral irradiance)  
 $R \dots m$  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).

$$R_{new} = RR_1 \quad (3)$$

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.

$$P = SERR_1 \quad (4)$$

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 irradiance  $E$  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 [11]. 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 [11] 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  $p$ .

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

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 [4].

$$S = S_{mean} + BS_{basis} \quad (6)$$

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. The spectral distribution was given by the manufacturer. Figure 2 shows the typical spectral distribution of TL-82 and TL-95 with slight differences between these two lamps.

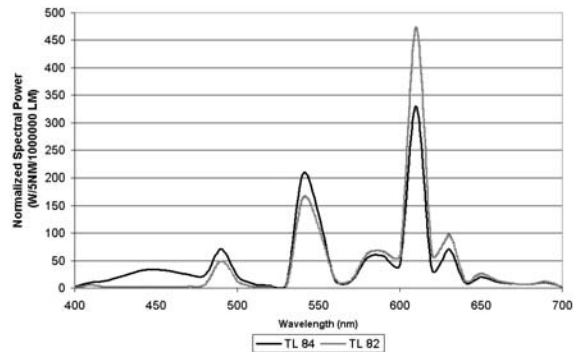


Figure 2: Spectral irradiance of TL-82 and TL-95

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 3 shows the spectral response curve of the DONPISHA camera. The data was provided by the manufacturer.

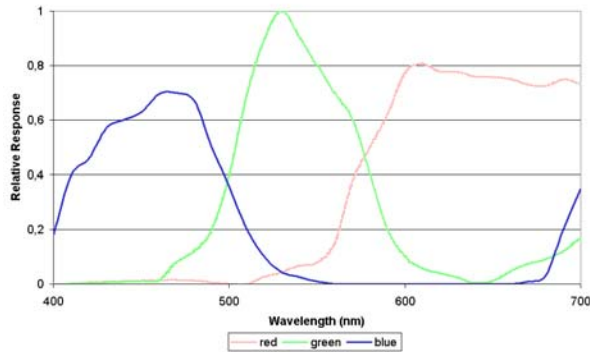


Figure 3: Typical spectral response of a Sony-camera

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 and is shown in Figure 4. 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.

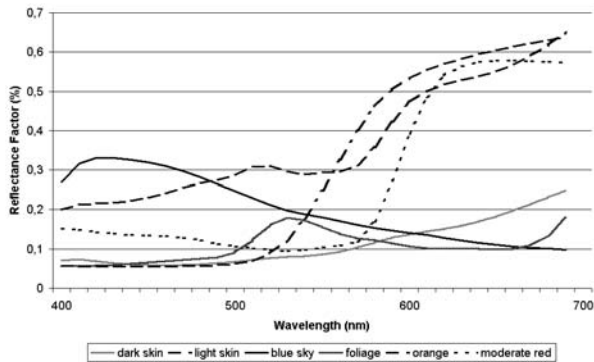


Figure 4: Measured spectral reflectances of 6 MacBeth color patches

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 5 shows two different test regions *A* and *B*.

#### 4. EXPERIMENTS

Two experiments are presented: the first example with MacBeth Colors and the second with real fragments. In the first experiment we use the measured

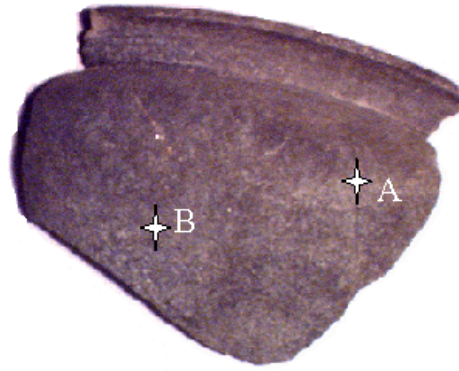


Figure 5: Test regions A and B

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 6 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.

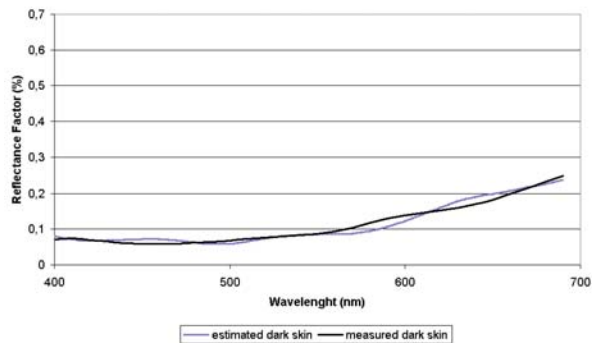


Figure 6: Measured and estimated spectral reflectance of a MacBeth Color Patch

In the second experiment we grab an image of a fragment and specify two test regions *A* and *B* (Figure 5). The reference set was chosen from the MacBeth color checker. The spectral reflectances of *A* and *B* are computed and visualized in Figure 7. For evaluation purposes we calculate CIE tristimulus values using a linear transformation and compare the achieved values with measured chromaticity coordinates 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.

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

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 chromaticity coordinates

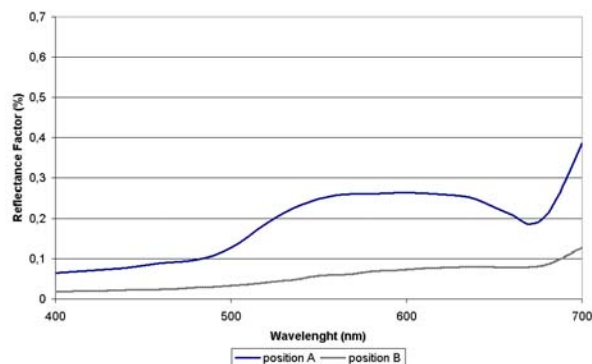


Figure 7: Calculated spectral reflectance of positions A and B

## 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 lighting 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.

## 6. REFERENCES

- [1] M. S. Drew and B. V. Funt. Natural Metamers. *Computer Vision, Graphics and Image Processing*, 56(6):139–151, 1992.
- [2] T. Gevers and W. M. Smeulders. Color-based Object Recognition. *Pattern Recognition*, 32(2):453–464, 1999.
- [3] M. Kampel and R. Sablatnig. On 3d Modelling of Archaeological Sherds. In *Proceedings of International Workshop on Synthetic-Natural Hybrid Coding and Three Dimensional Imaging, Santorini, Greece*, pages 95–98, 1999.
- [4] R. L. Lee. Colorimetric calibration of a Video Digitizing System. *Colour Research and Application*, 13(3):180–186, 1988.
- [5] 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.
- [6] C. S. McCamy, H. Marcus, and J. G. Davidson. A Colour-Rendition Chart. *Journal of Applied Photographic Engineering*, 2(3):95–99, 1976.
- [7] C. Menard and R. Sablatnig. Computer based Acquisition of Archaeological Finds: The First Step towards Automatic Classification. In Hans Kamermans and Kelly Fennema, editors, *Interfacing the Past, Computer Applications and Quantitative Methods in Archaeology*, number 28, pages 413–424, Leiden, March 1996. Analecta Praehistorica Leidensia.
- [8] C. Menard and I. Tastl. Automated Color Determination for Archaeological Objects. In *Is&E'T Fourth Color Imaging Conference, Scottsdale*, pages 160–163, 1996.
- [9] S. Nayar and R. Bolle. Reflectance Based Object Recognition. *International Journal of Computer Vision*, 17(3):219–240, 1996.
- [10] C. Orton, P. Tyers, and A. Vince. *Pottery in Archaeology*, 1993.
- [11] 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.
- [12] G. Wyszecki and W.S. Stiles. *Color Science: Concepts and Methods, Quantitative Data and Formula*. John Wiley and Sons, 2nd. edition, 1982.