RGB-D-λ: 3D Multispectral Acquisition with Stereo RGB Cameras

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Abstract: In this paper we report some key questions related to the acquisition of accurate color images adressed by the Colour and Space in Cultural Heritage (COSCH) project. We summarize the main criteria defined by COSCH Working Group 1 and used by the authors to help Digital Cultural Heritage (DCH) users to have a deepen knowledge and understanding of the constraints, preconditions and practical aspects related to the use of a multi-spectral acquisition system. We also report how color data can be estimated from spectral data and discuss several issues related to the measurement of reflective surfaces by 2D imaging systems.

1 INTRODUCTION

The paper introduces some key questions concerning the acquisition of accurate color images in Digital Cultural Heritage (DCH) identified through the "Colour and Space in Cultural Heritage" project (see www.COSCH.info), a trans-domain European Action (TD1201) supported, since 2013, by the European Cooperation in Science and Technology. The results reported in this paper were done in collaboration with the COSCH Working Group 1 (WG1) and will be included in the interim report of this working group which will be published on the next COSCH bulletin (see http://cosch.info/publications/). This work is part of a larger project in which the colorimetric accuracy of traditional devices characterized with state-of-the-art techniques (Bianco, Gasparini et al., 2008, Bianco, Schettini et al., 2009, Bianco, Bruna et al. 2011) is compared with multispectral devices (Bianco, Colombo et al., 2011).

The activities of WG1 are mainly focused on the "identification, characterization and testing of spectral imaging techniques in the visible and near infrared (IR) field" and on the "identification, characterization and testing of imaging techniques beyond the visible and short wave radiation" for the study and documentation of CH artefacts. Until now, most of the activities supervised by the WG1 have been dedicated to the use of spectral imaging techniques to the investigation of artworks, mainly 2-D objects such as paintings. Spectral imaging

systems are in general grouped in multi-band, multi-spectral and hyper-spectral systems depending on the number of bands selected over a given spectral interval and on their bandwidths. In the period 1989-2004, several projects (such as CRISATEL (Ribes, 2005), VASARI (Saunders, 1993) or NARCISSE (Lahanier, 2003)), or reports (e.g. see (Liang, 2004, Imai, 2010)) focused on the use of 2-D multi-band and 2-D multi-spectral imaging systems, shown the importance of spectral information to characterize 2-D cultural heritage objects in the visible field. In the last decade new developments in optical techniques led to novel ways of splitting the visible radiation (light). The COSCH WG1 decided in 2013 to explore the limits and advantages of the actual instruments in these wavebands. This WG1 defined a "Round Robin Test" (RRT) in order to compare color and spectroscopic measurements, as well as information on calibrated standards and laboratory mock-ups obtained through the use of diverse imaging devices or prototypes, specifically designed for high-quality digital imaging of artworks and for conservation purposes, developed by the different research groups that participate in the COSCH Action. In their preliminary works, WG1 members agreed that there are still no well-established and commonly accepted criteria and guidelines for the selection and the use of one of the above mentioned imaging systems. In this paper, we summarize the main criteria defined by COSCH WG1 and used by the authors to help Cultural Heritage users to have a deepen knowledge and understanding of the constraints, preconditions

689

and practical aspects related to the selection and the use of a multi-spectral acquisition system. Next, we report how color data can be estimated from spectral data and discuss several issues related to the measurement of reflective surfaces by 2D imaging systems.

2 ACCURACY OF 3D COLOR ACQUISITIONS

In (Boochs, 2015) the authors reported how to perform color acquisition using a multispectral system and what are the effects due to parametric factors (e.g. exposure time, camera response, etc.) and other external factors (e.g. spectral distribution of the lighting source) influencing the accuracy of color acquisition. They also reported how to evaluate the accuracy of a multispectral system and how to improve this accuracy by color calibration using a standardized color chart (e.g. the color checker chart). Other papers also addressed these issues, such as (Lopez-Alvarez, 2009, De Lasarte Rigueiro, 2009). Nevertheless there is still no well-established and commonly accepted criteria and guidelines for the selection and the use of standardized color charts for accurate color calibration of multispectral imaging systems. The number of color samples, the color gamut, the spectral distribution and the reflectance property of these samples are the four main factors influencing the accuracy of the calibration process. It is also important to remind that the color rendering of digitized images depends also of many other parameters, such as viewing geometry, lighting geometry, camera settings, etc. (Faridul,

2015). As example, in Figure 1, due to shadows, highlights, surfaces reflectance, viewing geometry, camera settings, color filters, etc. the scene digitized has different color appearances. As a consequence, for each viewing geometry used (i.e. each 2D color acquisitions) we suggest to apply again color calibration. As example, the scene shown in Figure 1 was acquired from 8 viewing positions (see Figure 2). In order to digitize this 3D scene with accurate color values, one solution consists: first to select sample colors on different object surfaces (as shown in Figure 3); next to calibrate each 2D view from the expected color values (using a sparse approach); and lastly to refine the color calibration (i.e. to minimize color differences) by color correction (using a dense approach). We suggest to use the solution proposed by H.S. Faridul et al. to minimize color errors between 2D views with high overlap (De Lasarte Rigueiro, 2009).

The results of the calibration process depends also of the material property of the color chart used, thus it is possible to obtain different values with one color checker chart or with another one. We experimented this with the color checked chart of the Round Robin Test, and two other color checker charts (used at Saint-Etienne and Milano).

To evaluate color differences between measured values and expected values, users can use the CIELAB ΔE metric or similar metrics such as the CIEDE2000. To evaluate spectral differences between measured (or estimated) spectral values and expected values, users can use the mean value and the standard deviation of difference values between spectral data. Another option consist to compute the percentage of the Integrated Irradiance Error metric (IIE(%)) which is a relative measurement of the

(a) Same scene viewed under four viewing positions and acquired with a RGB CANON camera sensor with a red filter (wide band filter) put in front of the camera.
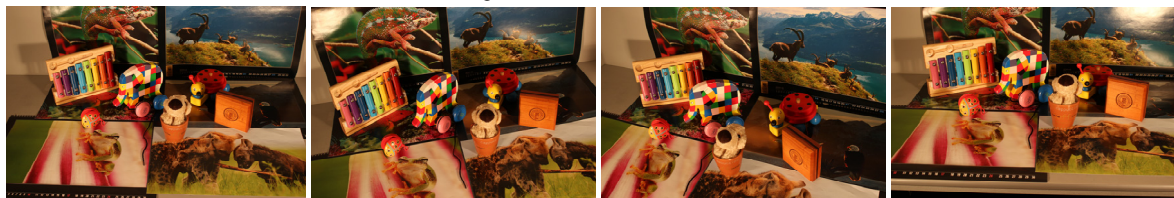
(b) Same scene viewed under four viewing positions and acquired with another RGB CANON camera sensor.

Figure 1: Example of a complex scene (composed of 3D objets put on and in front of colored planar surfaces) digitized by two cameras under different viewing positions.
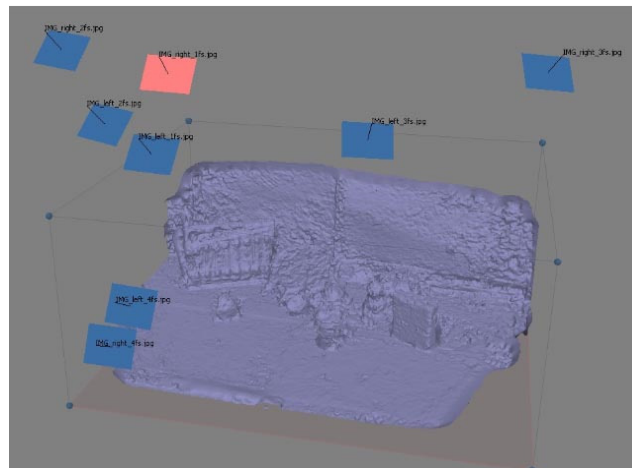
Figure 2: Screenshot of the dense reconstruction (922.000 points – 185.000 faces) of the 3D scene by the software Agisoft. The 8 positions of cameras used are illustrated by blue and pink squares.

Figure 3: Position of the 29 samples (manually selected in different areas) measured by the spectroradiometer MINOLTA CS1000.

difference in the total energy of the two spectral curves being compared (viggiano, 2002), or to use the colorimetric and spectral combined metric (cscm) (lópez-álvarez, 2005) which is based on the comparison of the spectra of natural illuminants from the colorimetric and spectral points of view.

3 RECOVERY OF REFLECTANCE SPECTRA FROM COLOR SENSORS

In the state of the art, several solutions are proposed to recover reflectance spectra from color values. Some solutions are based on 3D interpolation, 2D interpolation, non-negative matrix transformation or hybrid methods (Kim, 2012). In (Zuffi, 2008) Zuffi et al. demonstrated that the estimation of the spectra

of objects surfaces could be performed from data having lower dimensionality (e.g. from a RGB camera or from a generic N-filters camera responses). They proposed a solution, based on a linear model, which exploits the smoothness of surface reflectance functions. Several other methods, which also exploit the smoothness of surface reflectance functions, have been proposed to generate physically realizable natural spectra, while some additional limitations would constrain the recovered spectra (Peyvandi, 2011).

Several global optimization methods have been proposed to recover the spectra reflectance (Dupond, 2002). Recent works have improved the spectra recovery accuracy using local methods. In (Bianco, 2010) Bianco proposed a local optimization-based method which is able to recover the reflectance spectra with the desired tristimulus values, choosing the metamer with the most similar shape to the
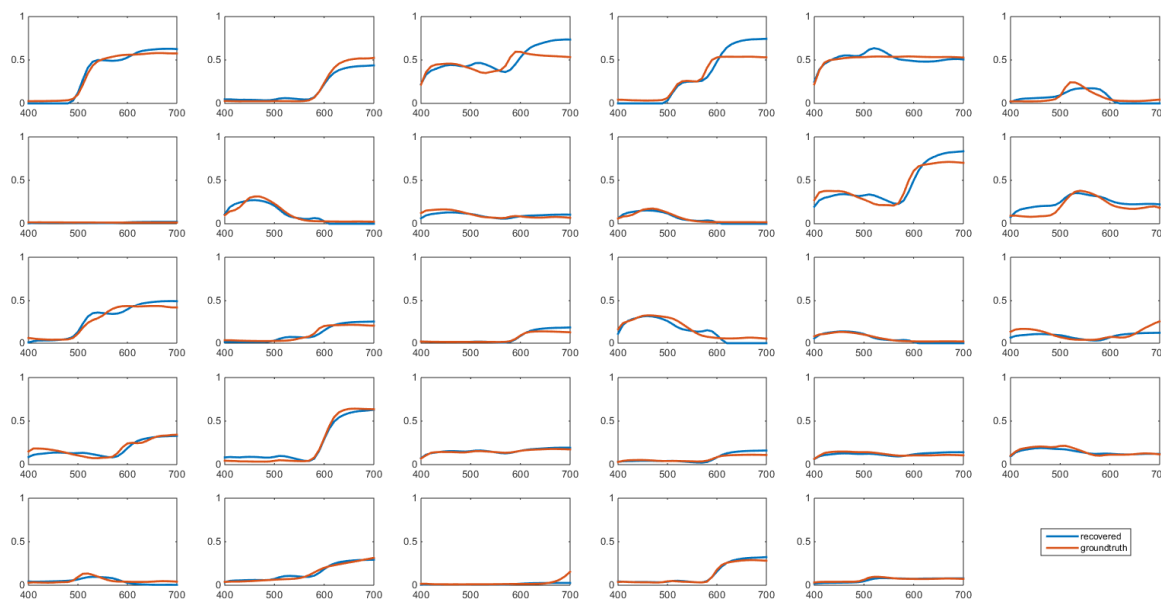
Figure 4: Recovery of the spectral distribution of the 29 samples selected in the scene considered.

reflectances available in a training set. The reflectance spectra of the Munsell Atlas, the Vhrel dataset, the Gretag MacBeth Color Checker CC, and the Gretag MacBeth Color Checker DC were used as samples in (Bianco, 2010).

In this paper we propose to recover reflectance spectra, from N optical filters put in front of a RGB camera sensor, using a two-step process. In our experiment we performed several tests in two different setups: i) using one large-band color filter and two color camera sensors (to simulate a 6 bands camera sensor, see example shown in Figure 1); ii) 30 narrow-band color filters and one monochromatic camera (see example shown in Figure 7). The idea is to combine the global optimization method proposed by Zuffi et al. (Zuffi, 2008) with the local optimization method proposed by Bianco (Bianco, 2010). Meanwhile the first method is used to initialize the recovery of the spectra reflectance, the second one is used in a second step to refine the recovery.

The method of Zuffi et al. (Zuffi, 2008) has been chosen as specifically designed to address the problem that reflectance spectra can be unfeasible: in fact the recovered reflectance can often present lobes outside the range [0%, 100%], or can present atypical spikes due to the reconstruction method or to the clipping of the recovered reflectance in the admissible range. The algorithm (Zuffi, 2008) starts with estimating the recovered reflectance through a linear combination of a spectral basis and then decomposing it into the parts of spectrum inside, above and under the admissible range, respectively.

An iterative procedure then starts to reduce the magnitudes of the parts above and below the admissible range. At each step, a smoothing procedure can be run on them. The procedure ends when the required accuracy or the maximum number of iterations has been reached.

The final recovery is performed using the method by Bianco (Bianco, 2010), using the previous one as initialization. The method (Bianco, 2010) has the advantage of using multiple spectral bases for the reconstruction. The basis is automatically chosen on the basis of the position in the color space of the sample to be recovered. The main steps of the method are reported in Figure 8, where V_0 and B are fixed basis, V_1 is the adaptive one, *GFC* is the Goodness of Fit Coefficient (Hernàndez-Andrés, 2001), and *p* is a value to be heuristically set.

The results shown in Figures 4 and 5 demonstrate that this solution is efficient. However, some errors are noticeable. For instance in Figure 4 for samples #3 (red sample on the ladybird at right), #4 (light pink sample on the elephant), #5 (pink sample on the elephant), #11 (blue sample on the wheel below the elephant) and #12 (pink sample on the wheel below the elephant). This is mainly due to the non-uniformity of these samples (reflective surfaces) and of their size (which was for some of them lower that the viewing field of the spectro-radiometer used). The Figure 6 shows the result of the 3D reconstruction obtained from the 6-bands camera sensor setup considered (from 8 viewing positions). We also performed 3D reconstruction
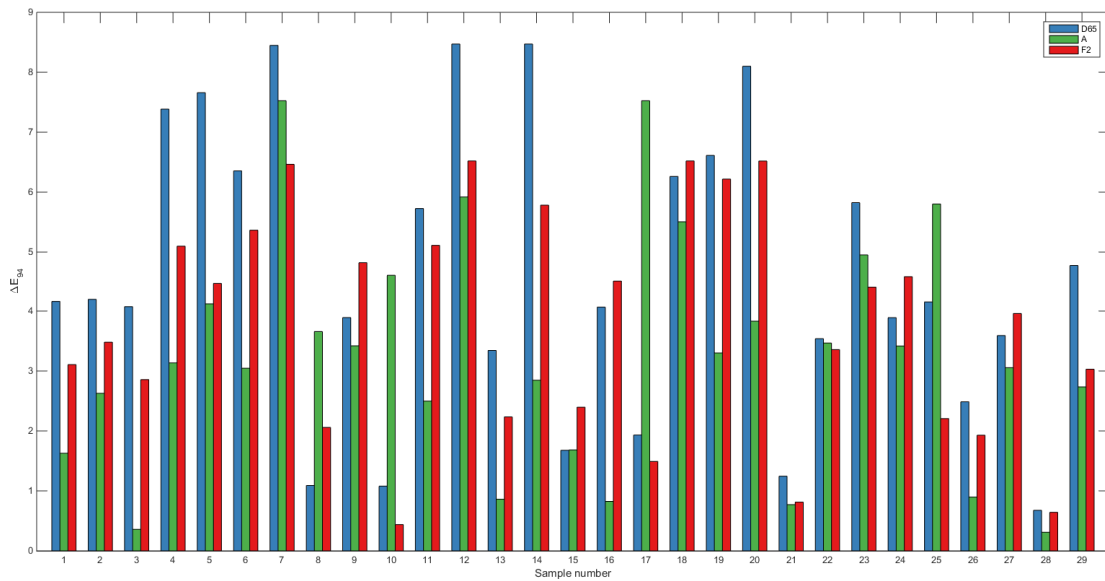
Figure 5: Computation errors between measured values (ground thruth values measured by the spectroradiometer) and estimated values. Depending of the object/surface properties (e.g. specular reflectance) and of the SPD of the light sources used, some ΔE94 values are quite low (e.g. the red sample below the ladybird at lelf, sample 21 or the brown nose of the dog, sample 28) meanwhile for other objects/surfaces (e.g. the yellow sample below the head of the ladybird at right, sample 2 or the blue sample of the elephant, sample 9) these values are higher.

Figure 6: Examples of 3D reconstruction of the scene considered viewed under illuimant D65 (a), or under illuminant F2 (b). White areas (i.e. holes) are due to occlusions between 3D objects and the background.

from the 30-bands camera sensor setup considered. In both cases results were satisfying.

We also performed 2D image reconstruction from the two setups considered (see Table 1 and Figure 7) in order to compare the accuracy of the two multi-spectral systems considered with the other multi-spectral systems used by other research laboratories having performed measurements for the COSCH WG1 on the "Round Robin Test". The results of these comparisons is under process. In both cases the acquisitions taken for the different spectral bands have been automatically aligned following the method described in (Bianco &

Cusano, 2011).

4 CONCLUSION

In this paper we introduced some key questions concerning the acquisition of accurate color images in cultural heritage applications inside the COSCH project. We summarized the main criteria defined by COSCH and used by the authors to help cultural heritage users to have a deepen knowledge and understanding of the constraints, preconditions and

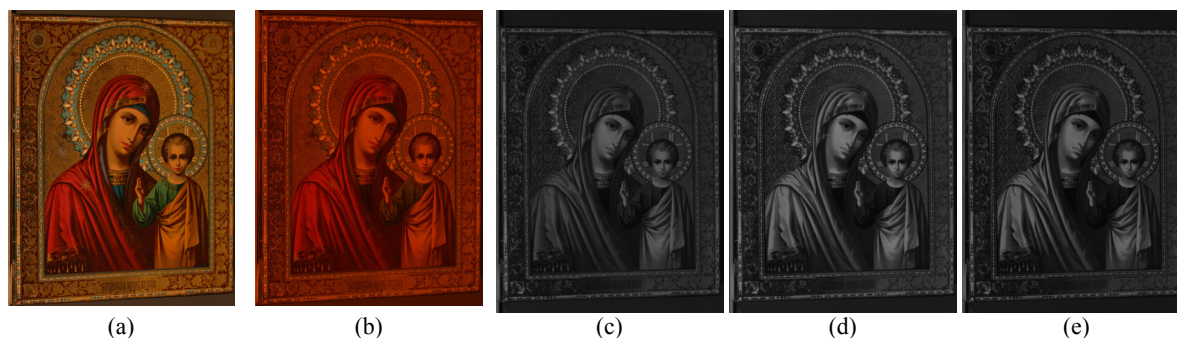|				
(a)	(b)	(c)	(d)	(e)

Figure 7: Example of a 2D scene (COSCH robin test ICON) digitized by : (a) a RGB CANON camera, (b) another RGB CANON camera sensor with a red filter (large band filter) put in front of the camera, (c) to (e) a monochrome camera with respectively a 400 nm, 450 nm and 500 nm filter (bandwith 10 nm) put in front of the camera. During our experiments we used: 30 optical filters (from 400 nm to 70 nm) of 10 nm bandwith and 3 optical filters of 100 nm bandwith to compare spectral distribution recovery form either a multispectral system based on 30 narrow-band filters or a multispectral system based on 6 wide-band filters.

Table 1: Report form defined by COSCH. Here we reported technical data related to measurement performed on the ICON shown in Figure 7.

Spectral imaging device details	Spectral region	Vis [400-700nm]	Vis [400-700nm]
	No. of bands	Vis 31	Vis 5
	Make and mode	The Imaging Source DMK41AU02. AS monochrome camera	Canon 1000D
		31 narrowband optical filters	coupled with a yellow wideband filter for the second shot
	Detector type	CCD	CMOS
	Details of any optics used in the acquisition (other than those part of the camera)	Nikon AF Nikkor 24mm f/2.8 lens with C-mount adapter	Canon EF-S 60mm f/2.8 Macro lens
	Capture settings (Exposure time, averaging etc.)	Different for each filter. from 5s to 1/5	1/160s for the first shot (unfiltered), 1/60s for the second one (filtered)
	Actual Spectral resolution	Spectral Resol: ~ 10 nm FWHM	N.A.
Details of illuminant	Type	2x ~3200K 500-Watt	2x ~3200K 500-Watt
	Details of illuminant spectrum	grey body radiator	grey body radiator
	Position of the analyzed target (vertical/horizontal)	45° on a stand	45° on a stand
	Working distance btw target and the system	100 cm btw target and lens	130 cm btw target and lens
	Angle btw targets and lights	approx 2x45°/0	approx 2x45°/0
	Reconstruction matrix (Y/N)	N	Y
	Calibration workflow (Capture to Reflectance)	Standard linear reflectance calibration on 99% reflectance spectralon plus non-uniformity correction with neutral gray card	Standard linear reflectance calibration on 99% reflectance spectralon plus non-uniformity correction with neutral gray card
	Description of related algorithms		reconstruction matrix computed using the acquisition of the MCC provided
	Noise reduction methods	none	2 reference image averages for the second shot

```
Begin
 Derive a basis V₀ for the whole training set
 Estimate the recovered spectra
 Calculate the spectral residuals between the
 recovered and the training set spectra
 Derive a basis B for the spectral residuals
 Use the basis V₀ to give an initial estimate of
 the recovered spectra
 for each initial estimate of the recovered spectra
 Do
  Calculate the GFC with the spectra in the training set
  Derive a basis V₁ for the spectra with GFC ∈ [p, 1]
  Use the basis V₁ to give an estimate of the spectra
  Compute the final recovered spectra
 End
End
```

Figure 8: Main steps of the spectral reconstruction method by Bianco (Bianco, 2010).

practical aspects related to the selection and the use of a multi-spectral acquisition system.

We also reported how color data can be estimated from spectral data and discuss several issues related to the measurement of reflective surfaces by 2D imaging systems.

As future work we plan to extend the spectral reconstruction to uncontrolled light setups, where a light estimation and correction step is needed to render the scene as taken under a canonical light (Bianco, Bruna et al., 2012, Bianco, Bruna et al., 2013, Bianco & Schettini, 2014). We will also investigate the use of more complex metrics to compare the acquisition taken with different devices: instead of using single-valued metrics, we will investigate the use of metrics able to output an error map combining both colorimetric and structural errors (Bianco, Ciocca et al., 2009). Often multispectral systems are calibrated using the Gretag MacBeth chart, which colors and substrate are not representative of those found in art. Sometimes even the use of an external chart is too invasive. Thus, we will investigate the use of techniques to design ad-hoc charts (Bianco & Schettini, 2012), even taking the optimal samples from the artifact itself. We also plan to investigate spatio-temporal effects, such as those reported in the ITN-DCH project (Makantasis, 2013, Kyriakaki, 2014, Doulamis, 2015) under uncontrolled light conditions.

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