Standard representation space for spectral imaging

Jean-Baptiste Thomas[Ω] [⋆], Pierre-Jean Lapray[†], Max Derhak[‡], Ivar Farup[⋆]
[Ω] **Université de Bourgogne, Dpt IEM, IMVIA, Dijon, France**
[†] **Université de Haute-Alsace, IRIMAS UR 7499, F-68100 Mulhouse, France**
[‡] **ONYX Graphics Inc., USA**
[⋆] **Norwegian University of Science and Technology, Department of Computer Science; Gjøvik, Norway**

Abstract

The variety of spectral imaging systems makes the portability of imaging solutions and the generalization of research difficult. We advocate for the creation of a standard representation space for spectral imaging. We propose a space that allows connection to colorimetric standards and to spectral reflectance factors, while keeping a low and practical dimension. The performance of one instance of this standard is evaluated through simulations. Results demonstrate that this space may show reduced performance in accuracy than some native camera spaces, especially instances with a number of bands larger than the standardized dimension, but this limitation comes with benefit in size and standardization.

Introduction

Several spectral imaging sensors provide data of a variety of dimensions and of various spectral quality. The variation spans from spectral radiance per wavelength at a given sampling, to a set of values corresponding to the integration of this radiance over a set of spectral filters, of which, color imaging is a specific subset. This variety of systems was a good asset for the development of spectral imaging solutions that could be tuned to specific applications. However, this diversity is a limitation when it comes to a generalization of use of this technique, in particular for computer vision and camera production scales. Several benefits may come from an increased level of standardization, e.g. communication, encoding, and algorithms.

Indeed, a generic representation of spectral data is not yet achieved, and the prevailing representation is normalised spectral radiance or spectral reflectance factors. This approach is correct and can be connected to many measurement standards (photometric, colorimetric, etc.). However, this representation is not practical to handle and researcher tends to reduce the dimension in many different ways before any processing or transfer. The only works we are aware of on addressing specifically this topic are 1-the attempts to create a virtual spectral space by Nambu et al. [38], 2-the description of the LabPQR space [11], and 3-the different standards of the remote sensing optical image products that are driven by the gears embedded on satellites for a specific mission (e.g. Landsat 8 or Sentinel 2). Note that the change from one product to another product [14] or their fusion [3] generates also some difficulties in this field. Yet these proposals are all quite limited, the first one due to the lack of optimization and acceptation though the underline idea is very relevant; the second one because the PQR part is based on principal component analysis and each of its axis has a specific dynamic; the later due to the remote sensing scope, constraints, and community-only use.

In this article, we propose to discuss the standardization of spectral data representation. We list the constraints we may want to enforce in such a standard, and provide hypotheses or approximations that could help the design of such a solution. The proposed solution only considers the visible range, but the near infrared, and potentially the short wavelength infrared, as well as some ultraviolet should be considered eventually. First, we discuss the need for standardization and give insight on the case of color imaging, then we discuss what already exist in spectral imaging. We propose a generic and pragmatic approach to the design of a standard. We then evaluate the proposal based on simulations, before concluding.

Standardization

Although tuning each sensor to specific applications allows efficient demonstrations of performance, the lack of standardization impacts several aspects of the use of spectral data. From a scientific perspective, it is difficult to conduct reproducible research. **Repeatability:** Data are captured by quasi-prototype sensors or limited editions, it is then difficult to reproduce the same results while using different cameras. **Benchmark:** There is no accepted benchmark data to evaluate any algorithms, except for some specific niches, since the sensors are designed specifically for a specific problem. This is true unless reflectance factors are used as data origin, but then the accuracy is unknown. **Dataset:** All the dataset are presented in the representation space of their capturing cameras, or, at the best, as reflectance factors estimated from the aforementioned camera raw data without any idea about the related errors. **Metrology, quantification of errors:** There is very little work related to the metrological aspect of the spectral image data and their quality, though this is a current research topic, e.g. [10] or [34].

From a practical perspective, many benefits may come from a homogeneous representation of data, such as **communication performance** at video rate. Indeed, recent sensing technologies allows for fast spectral acquisitions, with state-of-the-art speed, e.g. 60 fps. It is difficult to handle and process spectral data at this rate without defining efficient communication standards. This is related to the **storage** and image file format, since one spectral image size may vary from Megabytes to Gigabytes, which create challenges in storage, and access. Several recommendations were made for multispectral and hyperspectral image compression in space data systems [4] but efficient implementations in Very Large Scale Integrated technologies are needed for **codecs** to build inexpensive and integrated electronic circuits [40]. Up to date, there is no codec, to our knowledge, dedicated to spectral image reading or encoding, and this is directly related to the lack of standardization. Each software has their own format and processing, sometimes proprietary, e.g. ENVI [1]. In addition, there is an impact on the deployment of the technology in the different industry sectors. **Portability to field:** Most demonstrations are performed in laboratories and are difficult to deploy directly in the field, due to the camera device used to capture accurate data that often cannot be taken out in the field. **Applicability and generalisation of methods:** There is no evidence that the method demonstrated on laboratory data will perform outside of labs. **Learning and knowledge transfer:** Machine trained to perform with native sensor data are unlikely to perform on data captured by other devices. **Market size:** The industry who designs data analysis solutions cannot really invest time on the creation of one solution per camera.

These problems were introduced at the CCIW-interim conference in June 2022 in a keynote given by J.B. Thomas [2]. This was followed by discussions on that topic during a meeting of the CIE research forum RF-01, Spectral Imaging [3], where it is under discussion to push this problem to a CIE Technical Committee.

The case of color imaging

Spectral sensitivities of color imaging sensors

Many different spectral sensitivities are used in color cameras [16] [4]. Moreover, in the wide range of available camera models, color imaging is not limited to 3 bands [36] since additional bands permits to solve metameric mismatch between the Human Visual System (HVS) and the camera system, i.e. the non respect of the Luther and Ives conditions [31] on the camera spectral sensitivities. Nevertheless, even in this case the image data are transformed into an RGB space to be used as color images. In several applications and publications, we also observe that the camera sensitivities are not really at the heart of the discussion anymore (at the inverse of the case of spectral imaging). Even in camera authentication, it is mostly noise patterns or proprietary algorithms artifacts that are analysed -e.g. demosaicing [2]-, rather than the spectral sensitivities. Applications in computer vision seems to suffer marginal impact from the RGB sensitivities [30]. Remaining discussions on the sensitivities are limited to the limit of the metameric imaging pointed out by Koning and Herzog [20].

Imaging Pipeline

The raw color sensor data are indeed subject to several transformations before delivering an RGB color image. Typically, the imaging pipeline is composed by some pre-processing steps, such as dark noise correction and other noise removal, and by some demosaicing when appropriate. Another processing handle the illumination, i.e. white balance, within which, it is possible to modify the sensor spectral definition to improve the result on the illumination correction, i.e. spectral sharpening [12, 13]. This is coupled with a color transform that finally matches the image to a standardized RGB space, that can be proprietary (Adobe) or generic (sRGB). The use of RGB as a standard conceptual representation space allows the intuitive use of color images. Even without a physical calibration, color images are relatively calibrated toward illumination and spectral sensitivities via the use of color transforms and white balance.

Spectral imaging

The numerous spectral imaging systems (see for example cameras proposed by PixelTeq, Ximea, Silios, Norsk Elektro Optikk, Specim, Spectraldevices, etc.) lead to problems in the communication of spectral data. In particular, the use of snapshot camera allows for real time imaging and applications in computer vision. e.g. spectral filter arrays [24]. In such applications, it is critical to establish communication protocols compatible with all the different solutions.

Imaging Pipeline

In the case of snapshot spectral imaging, the imaging pipeline can be very similar to the one of color imaging [23]. Denoising, demosaicing can also be applied when necessary, or registration between bands in the case of sequential acquisitions. The illumination is handled through spectral constancy. In the easiest lab configuration, this is a static transform established at a calibration process with the use of a highly diffusing material of known reflectance factors (e.g. Spectralon). It is also possible to embed a mechanism similar to white balance for color camera. This is defined in a series of articles by Khan et al. and is based on illumination estimate [17], followed by a spectral adaptation transform [18], which result in a stable spectral representation despite of the change of illumination [19]. From a limited number of bands of arbitrary sensitivities, it is also common to either apply a color transform or a spectral reconstruction, which allow to describe the data into standard representation spaces, either colorimetric or as spectral reflectance factors (e.g. linear method [33], Wiener [42], Matrix R [47], polynomial [9], fuzzy logic [32], etc.). The resulting spectral image can be stored such as indicated in the Technical Committee 223:2017 [6].

Dimensionality reduction

The general use of spectral imaging suffers yet from the quantity and diversity of data. A large body of literature focuses on dimensionality reduction for specific analysis. For example, Principal Component Analysis is widely used to reduce the number of necessary bands for data classification. However, for standardization, designing a space based on PCA is not optimal due to the inhomogeneous distribution of information over the specific dimensions [38]. Dimension reduction is also applied for visualisation of spectral images as color images. This is done by e.g., the selection of three bands [25, 45, 1, 29, 39], the maximisation of the information on three false color bands by e.g. PCA [15] or Wavelet [41] decomposition. The fusion of information toward a color image or a panchromatic image is also considered [21, 28, 27]. The effect on the application is studied in an article [35], where it is shown that dimension reduction methods impact on the performance of classification. Generally it is difficult to answer the question on the number of the necessary dimensions. Quantitative studies have been carried out in the literature to evaluate the spectral and colorimetric accuracies of several spectral imaging systems (e.g. [46]). At least for these two goals, the answer depends on the nature of the bands, on the computational method used and on the performance on application, so no

[1] https://www.l3harrisgeospatial.com/docs/enviheaderfiles.html

[2] https://gdr-appamat.cnrs.fr/amp/evenement/computational-color-imaging-workshop-cciw-interim/

[3] https://cie.co.at/researchforum/rf-01

[4] https://nae-lab.org/ rei/research/cs/zhao/database.html, accessed 08/06/2022.

general consensus is yet found.

Transmission and real-time interactions

Spectral imaging systems produce data that have a high spatial, spectral and temporal resolutions, since an image of a decent spatio-spectral definition would typically be several gigabytes, including a fair amount of correlation. It introduces challenges in the ability to transmit and interpret the spectral images efficiently, where the limitation is in the loading and transfer of the spectral data [8]. Some existing practical implementations need high performance computing technologies, e.g. parallel and distributed computing, which are expensive, difficult to implement and of limited portability. Yet, several demonstrators have shown that colorimetric representation and interaction with spectral image data can be performed in real time, by using Graphic Processing Units [7] or by having most of the computation done by a combination of web technologies [8].

Proposal

Criteria for a standard space

The proposed space should be based on specific criteria, related to HVS, information content and practical constraints.

- The standard should allow for fast and accurate colorimetric and vision models link. Thus, it must have a solid relationship to the HVS. In particular, the first bands would relate to color so fast color visualisation would be possible without loading the entire data.
- It should allow for excellent spectral reproduction, i.e. relates to spectral reflectance or radiance factors, while remaining of low dimension.
- Be adequate for a wide range of intervals of the electromagnetic spectrum. It must cover at least the visible range, but should probably extend to the near infrared, the ultraviolet and potentially the SWIR. However, too much emphasis put into sampling non-visible wavelengths may sacrifice spectral reproduction characteristics in visible range or increase the dimension.
- The full expression of the standard should also provide methods to transform standard values into color and into reflectance factors. These methods should allow for a control on and a tracking of the error induced.
- The standard should be compatible to established communication protocols.

Methods to design a standard space

There are many approaches to designing such a space, and candidates are infinite at this stage. In this article, we propose an ad-hoc description of a potential standard. We do not pretend that it is optimal, but we want to establish the basis for further discussion.

In fact, it seems important that the proposal includes the photosensitive cells of the eye, LMS for the cones and the scotopic $V(\lambda)$ for the rods (noted $SV(\lambda)$ here), so it relates directly to the HVS. In such ways, depending on the choice of LMS and $SV(\lambda)$, the compatibility of the standard with a colorimetric and a photometric standard is built in. Besides, in order to span the rest of the visible range in the best way, we propose to create one curve closer to the UV, this is done by shifting a copy of the S curve toward UV, and for the higher wavelengths, we simply created a generic function that we slide. This function is a $(L+M)/2$, and is chosen arbitrarily. Note that it seems important that the standard is a potential realisable instance of a sensor and intuitive enough, and so its spectral definition should not contain negative values (exclude PCA and metameric blacks), and be mostly monomodal (exclude the direct use of CIE-XYZ).

We study one instance of this standard in the remaining of this paper. We decided to pick 8 bands in total, spanning the visible range. We used the 2 degrees LMS from Stockman and Sharpe [44, 43], as presented in http://www.cvrl.org/. We also include the rod sensitivities, i.e. the scotopic luminosity function from CIE-1951 [5], data from the same website. The resulting virtual sensor is shown in Figure 1. Its peak sensitivities are shown in Table 1.

Peak (nm)	413	443	505	542	570	612	673	735

Rounded peak sensitivities values of the instance of the standard space studied in this article.

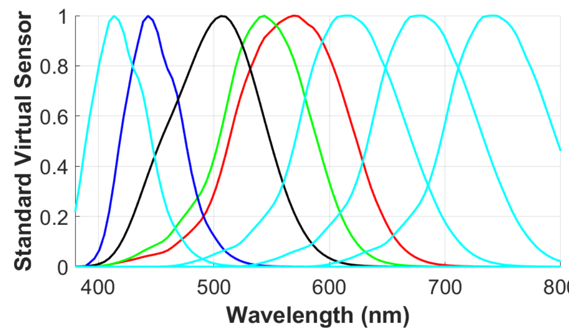

Figure 1. *Instance of the standard space proposal defined in the electromagnetic space and normalised for energy. RGB stands for LMS, and the black curve for $SV(\lambda)$.*

Methods to transform raw spectral data to the standard space

Standard data can be computed from the sensor raw domain by creating an orthonormal basis of the sensor subspace. This is done by applying a Gram–Schmidt QR decomposition [22].

Let us say that the sensor has N dimensions (later in the experiment, S_3, S_5, S_8, S_{12} and S_{16}). Given the spectral resolution of M for spectra, the sensor is defined by an $M \times N$ matrix $\mathbf{S}$.

Given a representative dataset of (e.g. Munsell) spectra $\mathbf{p}$ with a resolution of M, we can find a projection of $\mathbf{p}$ to the subspace spanned by the N sensors. To this end, we make an orthonormal basis of the sensor subspace, by applying a Gram–Schmidt QR decomposition to $\mathbf{S}$:

$$\mathbf{S} = \mathbf{QR} = \begin{bmatrix}\mathbf{Q_1} & \mathbf{Q_2}\end{bmatrix} \begin{bmatrix}\mathbf{R_1} \\ 0\end{bmatrix}, \tag{1}$$

where $\mathbf{Q}$ is an $M \times M$ orthogonal matrix, $\mathbf{Q_1}$ an $M \times N$ matrix with orthonormal columns spanning the same space as the columns of $\mathbf{S}$, $\mathbf{Q_2}$ an $M \times (M-N)$ matrix with orthonormal columns spanning the null space of $\mathbf{S}$, $\mathbf{R}$ an $M \times N$ upper triangular matrix, and $\mathbf{R_1}$ an $N \times N$ upper triangular matrix.

To project the individual pixel spectrum $\mathbf{p}$ onto the sensor subspace, and reconstruct a pixel spectrum represented as a column vector $\mathbf{p'}$, we use the raw sensor data I ($\mathbf{I'} = \mathbf{S^t p}$):

$$\mathbf{p'} = \mathbf{Q_1}(\mathbf{R_1^t})^{-1}\mathbf{I'} \, , \tag{2}$$

Then, to compute the standard value, it is enough to apply the projection of $\mathbf{p'}$ to the standard sensor:

$$\begin{bmatrix} Std1 \\ ... \\ Std8 \end{bmatrix} = \mathbf{C^t p'} \, , \tag{3}$$

where $\mathbf{C}$ ($M \times 8$) are the spectral sensitivities of the standard virtual sensor.

To perform a spectral and a colorimetric analysis of the performance, we used linear models[5], trained on the same data, that compute colorimetric values or spectral reconstruction from the standard data or from the sensor data. It is also very useful and fast to compute a colorimetric image from only the three first bands of the standard (the *LMS*). In practice, this will reduce the access to data for fast color visualisation of spectral images. For that, we created another linear transform from the three standard *LMS* to colorimetric values (XYZ1931). Note that if the XYZ2006 are used, the linear transform from Shape and Stockman's *LMS* to XYZ2006 is embedded in the standard. In our case we could not do it because we want to evaluate the quality of the transform with ΔE^*_{76}. It is important that a color distance is developed over the XYZ2006 standard in the future. One of the advantage of our proposal, is that it conceptually remains untouched across evolution of the colorimetric standard, as long as it is based on a given version of *LMS*.

Methods to test the quality of this space

An ad-hoc test would be to consider a metric and a dataset. Since the proposal has no spatial information, it can be based on point-wise spectral measurements and simulation of sensor acquisition. We decided to work on Munsell reflectance data [37], downloaded from the Joensuu website [26]. In terms of metric, the color difference could be measured by any of the recommended color differences that are compatible with the standard definition, while in the case of spectra, the topic is more subject to discussion. Accepted signal processing metrics such as the peak signal-to-noise ratio should be considered, as well as magnitude independent metrics, such as the goodness of fit coefficient, so we displayed both. However, it is understood that all of these metrics might be limited, especially when it comes to provide interpretation on the error value and its impact on applications.

Results

In order to demonstrate our proposal, we consider the Munsell reflectance spectra illuminated by a D65 illuminant, we consider the visible range $[380, 800]$ nm with a sample every 4.2 nm. Hypothetical sensors based on Equi-Gaussian filters are simulated and capture this data. Figure 2 shows two instances of these sensors. We generated Sensors from 3 to 16 bands, referred to as S_3 to S_{16}. For conciseness, only results for 3, 5, 8, 12 and 16 bands are shown. The standard itself is used as a sensor too for reference.

[5] Though the transform from Sensor to Standard is deterministic, spectral reconstruction and colorimetric transforms need to be learned.

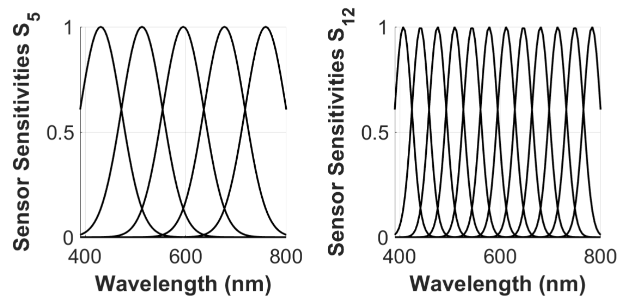

Figure 2. *Examples of spectral definition of sensors considered in our experiment, on the left for 5 bands and on the right for 12 bands.*

From there, we split the data in two, 50% become a training set and the other 50% the testing set. The general experiment is displayed in Figure 3.

First, the transforms indicated in the previous section are computed using the training data. Then, we apply spectral reconstruction and color estimation from 1-the standard data, 2-the sensors data, 3-the sensors data are transformed into the standard space and the standard transform is used to estimate the spectra and the color. These three cases are compared versus the ground truth that are the Munsell colorimetric values under the $D65$ illuminant, and the Munsell radiance. For color, we computed the CIE ΔE^*_{76}. For spectra, we computed the *RMSE* (Root Mean Square Error) and the *GFC*. In all the cases, we present the average error, μ, and the standard deviation σ. Results are shown in Table 2.

Results show that if the sensors have a lower dimension than the standard, the use of the standard does not generate loss in performance. However, when the sensor is of very high dimension, the loss of dimension implies a loss of performance compared to the direct use of the sensor, rising the question if such standard should be always used. In some cases though, results are better than the standard as reference, so some information from the higher dimensions of the original sensor is preserved - this mostly happens for spectral reconstruction. This smooth behavior is also coming from the fact that we used only Gaussian filters in the simulation, these filters are not so different from the standard proposed. The color estimate from only the *LMS* bands of the standard are also very competitive up to 8 bands. This is because the *LMS* used are not 100% compatible with the colorimetric model used, when we switch to CIEXYZ2006, there should be no difference because the first three bands would be colorimetric.

Conclusion

We proposed a definition for a standard representation space for spectral imaging. This standard could be adapted in terms of number of bands to be optimal in spectral reconstruction. It can adapt also to follow colorimetric evolution. This proposal allows for a fast colorimetric visualization of spectral images as color images.

The instance of this standard studied in this article demonstrates the feasibility of the implementation. Results from state-of-the-art data and methods demonstrate that the gain might be worth a reduction of performance in spectral reconstruction for highly resolved sensors. These results need to be confirmed on other, realistic, sensors spectral definition, with more or less over-

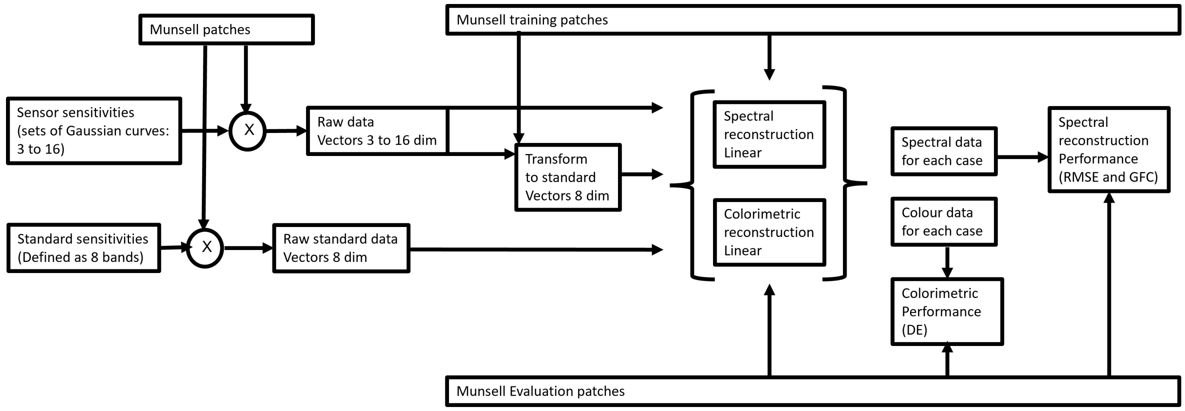

Figure 3. *Experimental workflow to investigate the standard proposal.*

		Performance			
		Color	*Color$_{direct}$*	Spectral	
		ΔE^*_{76} (μ/σ)	ΔE^*_{76} (μ/σ)	*RMSE* (μ/σ)	*GFC*
S_3	**Raw_3**	9.82 / 21.26	- / -	26.28 / 16.86	15.22
	Std_3	13.74 / 10.67	13.88 / 10.90	26.28 / 16.86	15.22
S_5	**Raw_5**	3.51 / 3.11	- / -	14.82 / 7.78	8.16
	Std_5	7.47 / 5.21	7.13 / 5.40	14.82 / 7.78	8.16
S_8	**Raw_8**	0.53 / 0.44	- / -	7.96 / 4.50	4.46
	Std_8	0.73 / 0.43	0.74 / 0.61	7.96 / 4.50	4.46
S_{12}	**Raw_{12}**	0.10 / 0.05	- / -	3.59 / 1.72	1.94
	Std_{12}	0.18 / 0.08	0.57 / 0.56	6.94 / 3.99	3.90
S_{16}	**Raw_{16}**	0.03 / 0.02	- / -	2.38 / 1.05	1.27
	Std_{16}	0.16 / 0.08	0.58 / 0.55	7.14 / 4.01	3.99
Standard		0.05 / 0.04	0.53 / 0.59	7.20 / 3.95	4.00

Evaluation of the proposal based on simulations over different scenarios.

lap and of different shapes.

The case of the near infrared was not considered in our proposal, future work should address this part since many of our spectral sensors capture VNIR information. We hope that this topic will be further discussed within a Technical Committee of the CIE. In fact, fundamental discussions related to a standard space and to the methods to build it needs to be conducted by our community in order to achieve a consensus. Other aspects can be considered in the future to help to keep track of accuracy, such as the point spread function for each of the sensor band.

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