Standardization of spectral imaging:
What is the RGB of spectral images?

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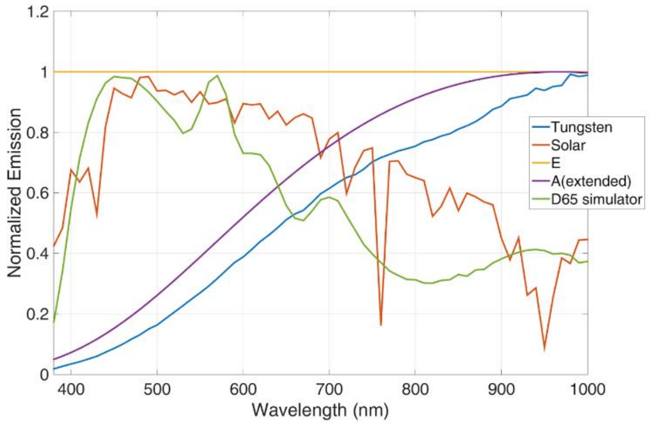
Spektralion AS

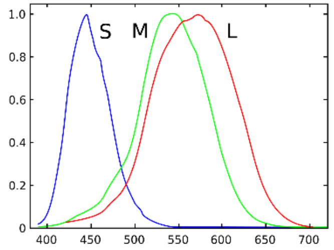
…The quest for a conceptual (and practical) representation of spectral data…

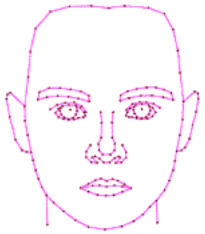
- Explanations
- Challenge & Partial answers
- Discussions

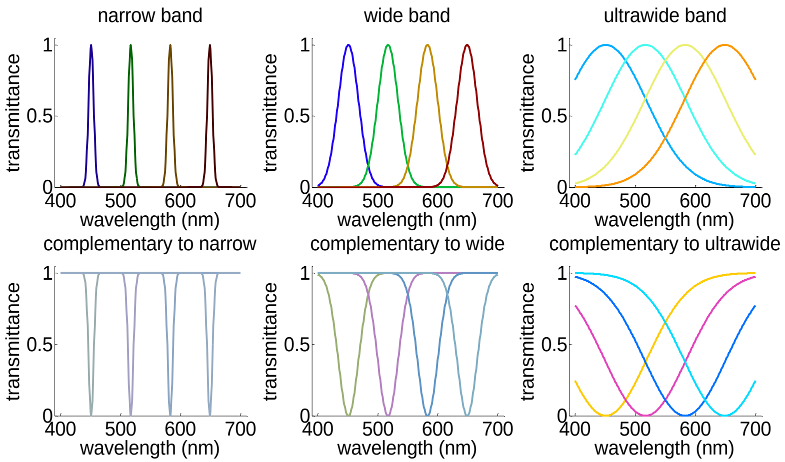
Flat, matte and diffuse models

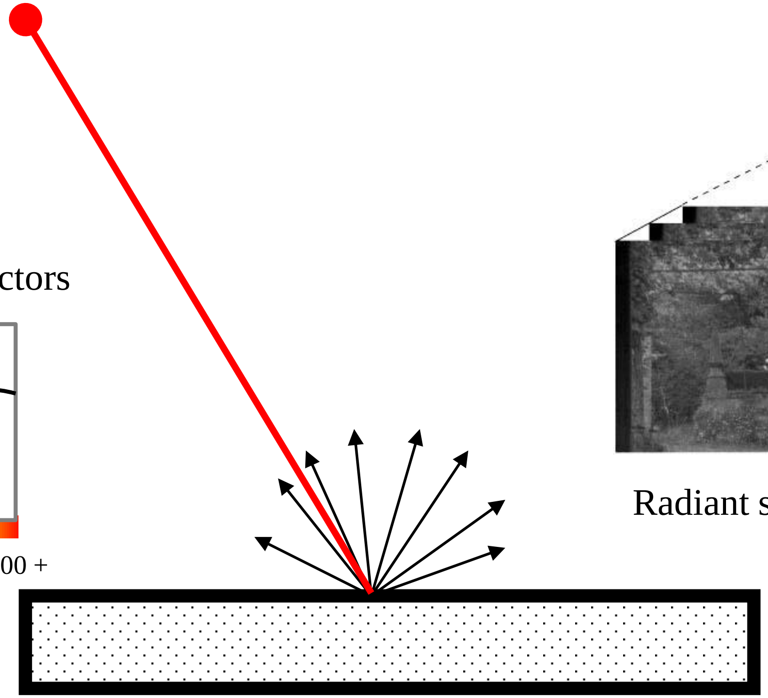


https://fr.m.wikiversity.org/wiki/Fichier:Cones_SMJ2_E.svg

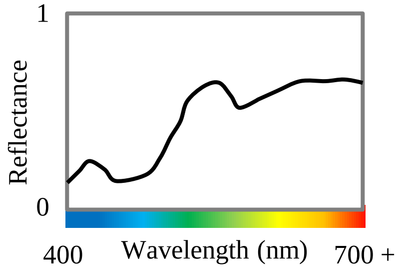


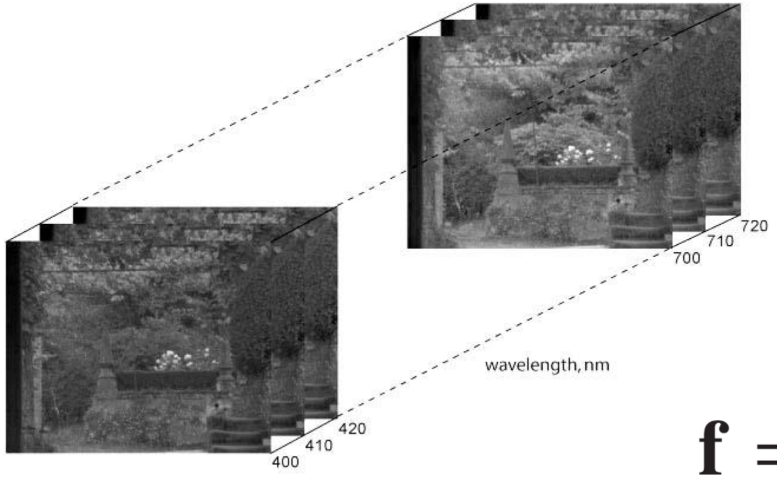






Spectral reflectance factors



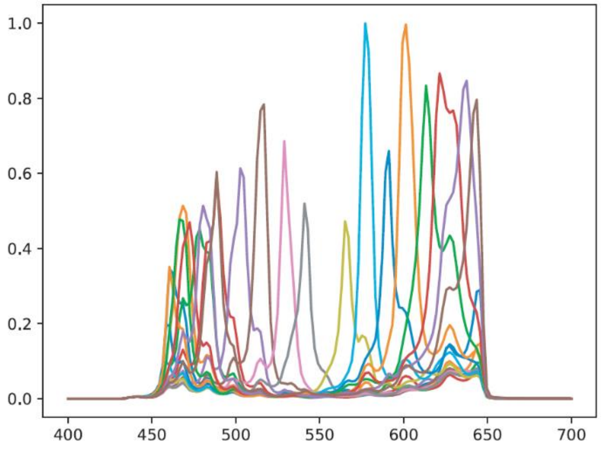


Radiant spectral power distribution

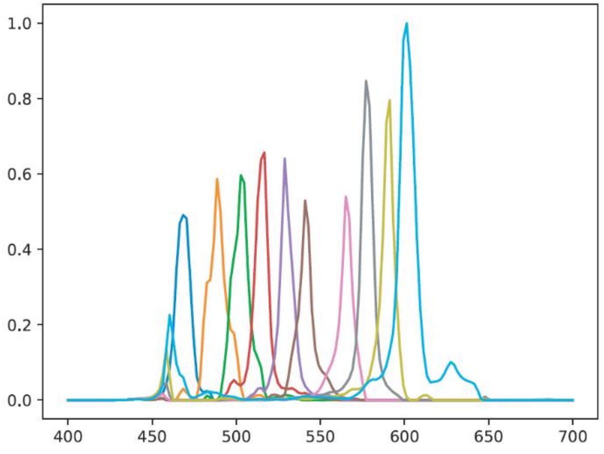
$$\mathbf{f} = \int_{\omega} e(\lambda) r(\lambda) \mathbf{c}(\lambda) \mathrm{d}\lambda$$

$$\mathbf{F} = \mathbf{REC}$$

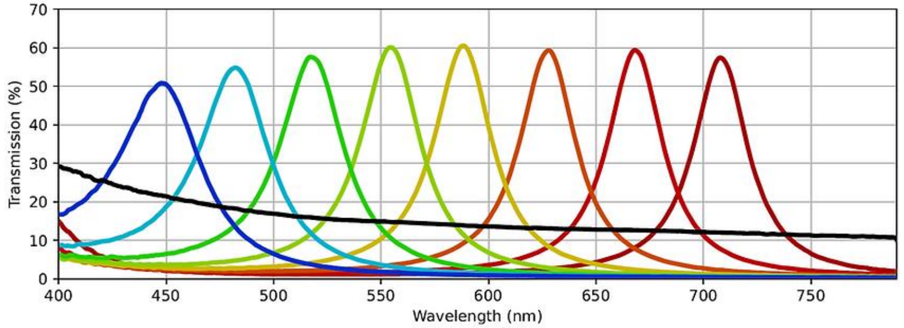
A diversity of spectral imaging



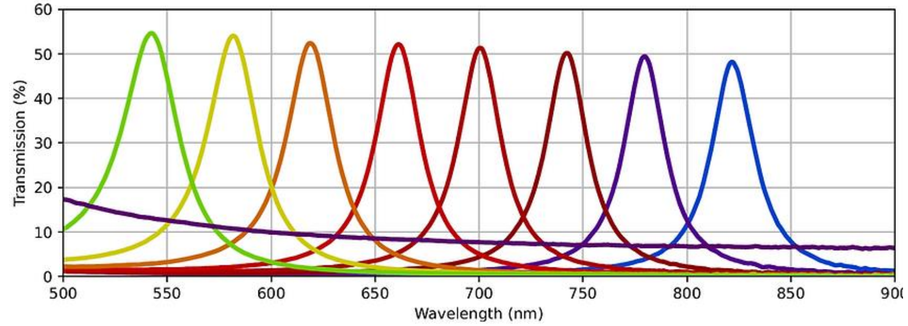
XiSpec, Ximea



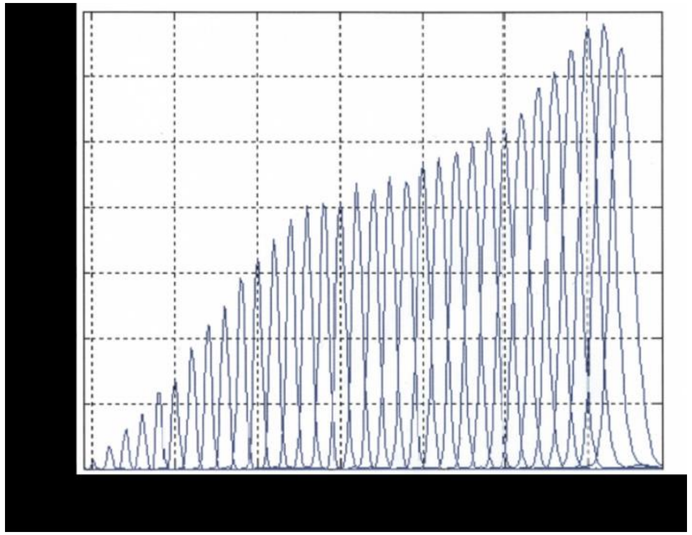
XiSpec, CorXimea



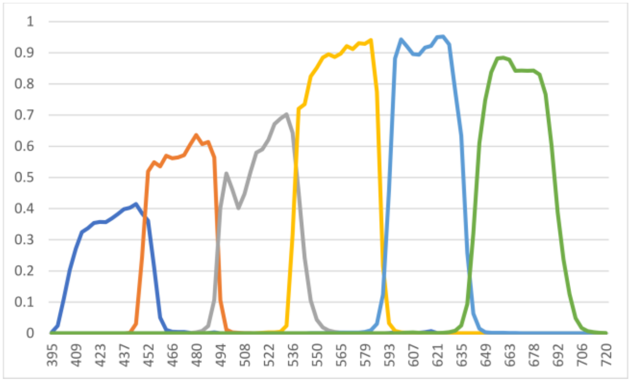
SILIOS, CMS-C



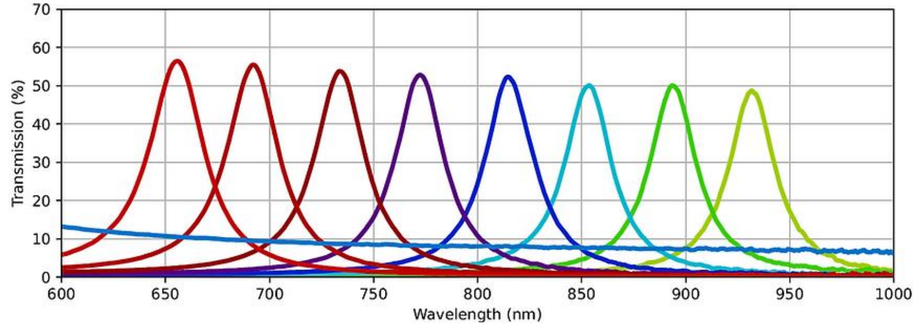
SILIOS, CMS-V



VariSpec LCTF filters

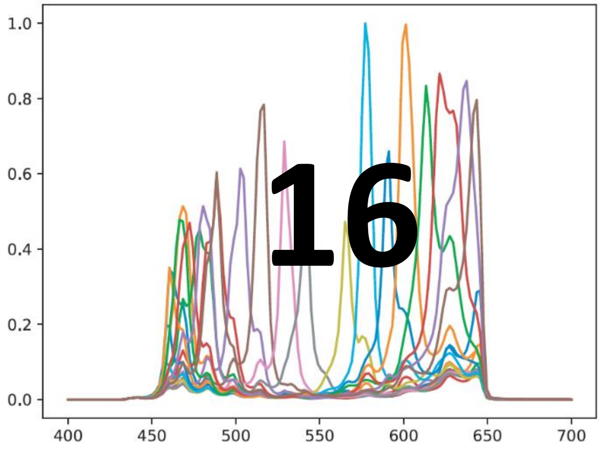


Pixelteq Spectrocam™

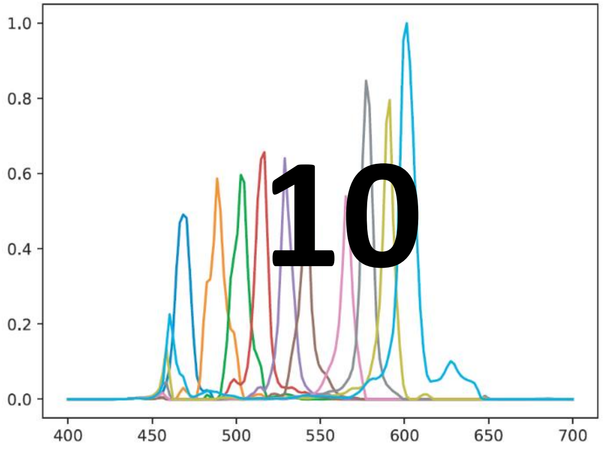


SILIOS, CMS-S

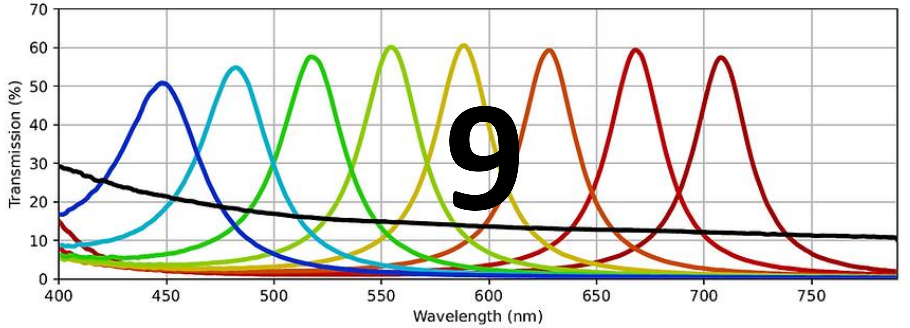
A diversity of spectral imaging



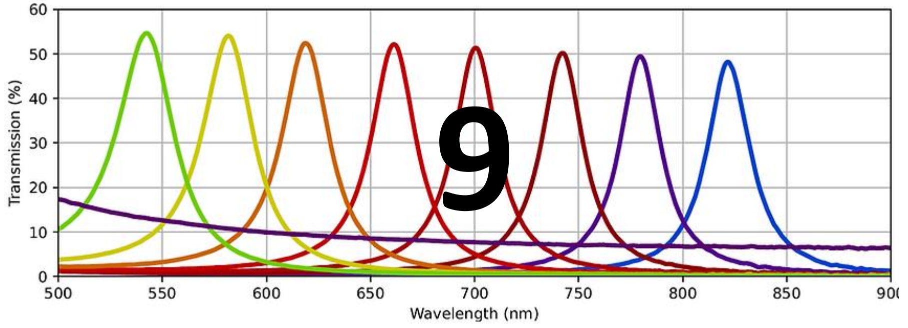
XiSpec, Ximea



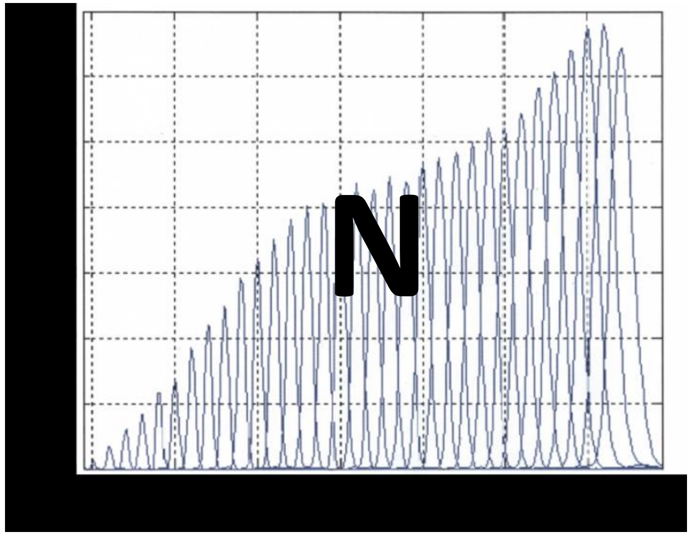
XiSpec, CorXimea



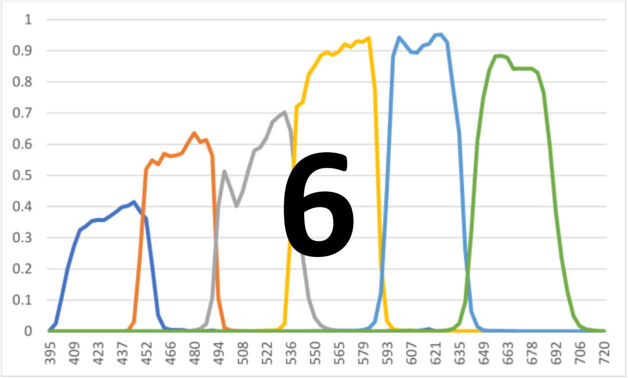
SILIOS, CMS-C



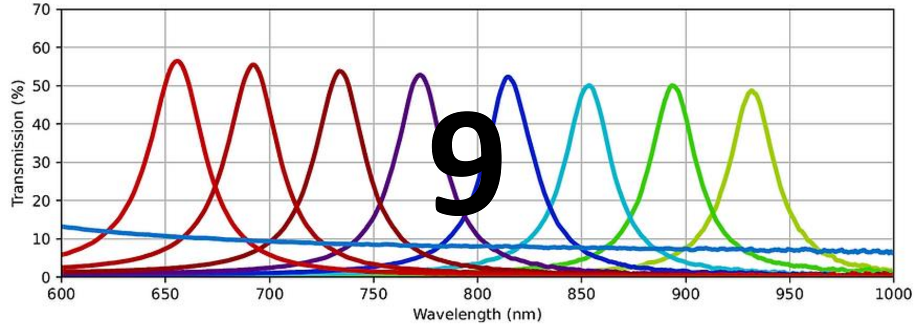
SILIOS, CMS-V



VariSpec LCTF filters



Pixelteq Spectrocam™



SILIOS, CMS-S

Issues related to this diversity

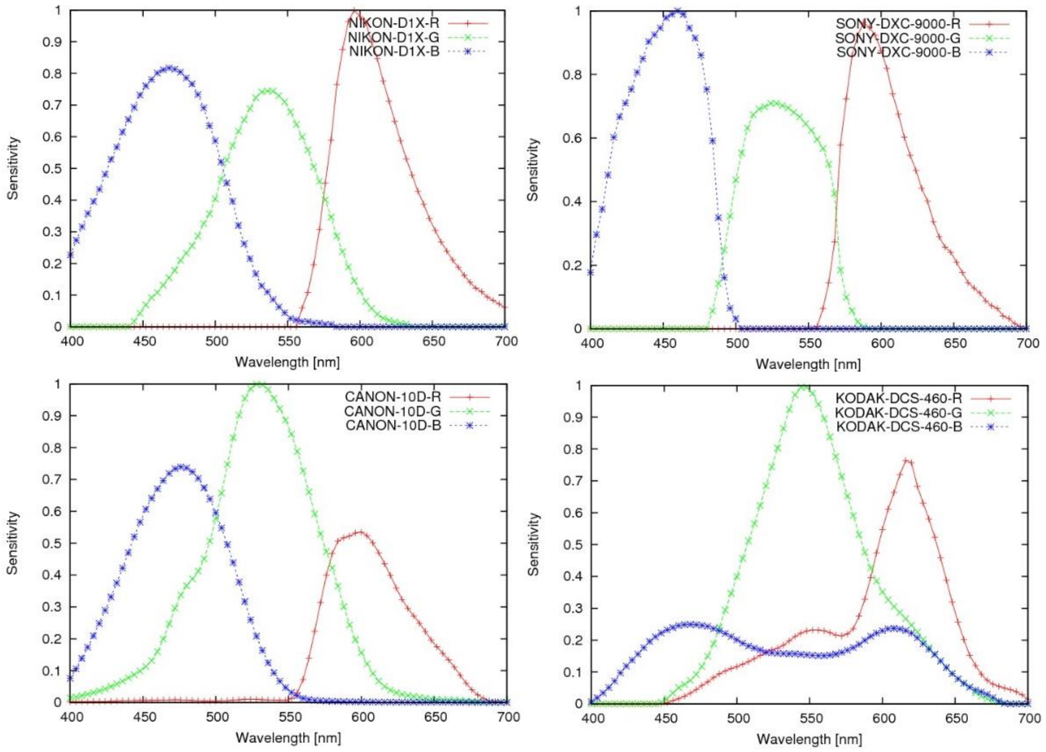
- Scientific perspective
  - Repeatability
  - Benchmark
  - Dataset
  - Metrology, quantification of errors
- Practical aspects
  - Communication performance
    - Video rate
  - Storage
  - Encoding
- Industrial development and deployment
  - Portability to field
  - Applicability and generalisation of methods
  - Knowledge transfer
  - Learning
  - Market size
- …

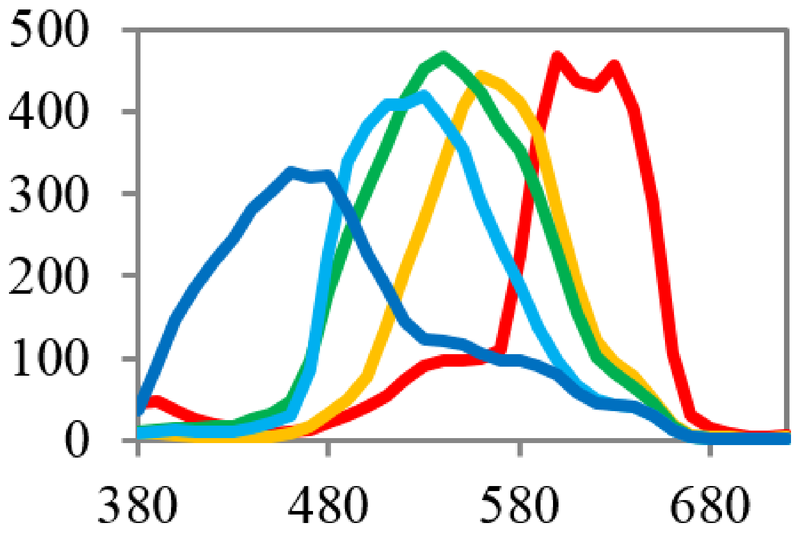
Once upon a time…

…And we believed we would design one sensor for each application.

How is it adressed in Colour imaging?

- Several spectral sensitivity sets but only one space of representation



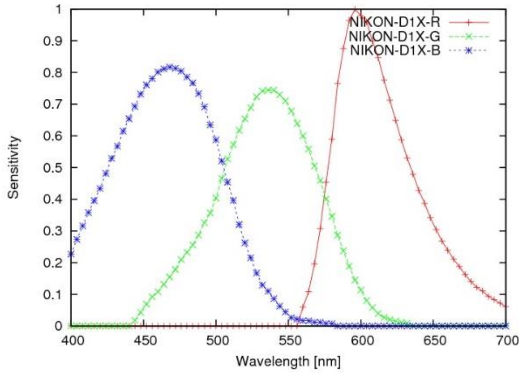


Kawakami, R., Zhao, H., Tan, R.T. *et al.* Camera Spectral Sensitivity and White Balance Estimation from Sky Images. *Int J Comput Vis* **105,** 187–204 (2013). https://doi.org/10.1007/s11263-013-0632-1
https://nae-lab.org/~rei/research/cs/zhao/database.html

Y. Monno, S. Kikuchi, M. Tanaka and M. Okutomi, "A Practical One-Shot Multispectral Imaging System Using a Single Image Sensor," in *IEEE Transactions on Image Processing*, vol. 24, no. 10, pp. 3048-3059, Oct. 2015, doi: 10.1109/TIP.2015.2436342.

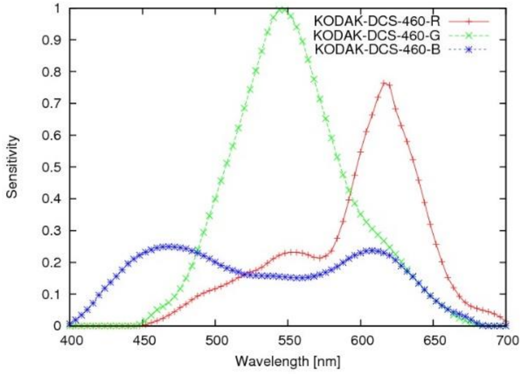
Sensor RGB and Perceptual RGB

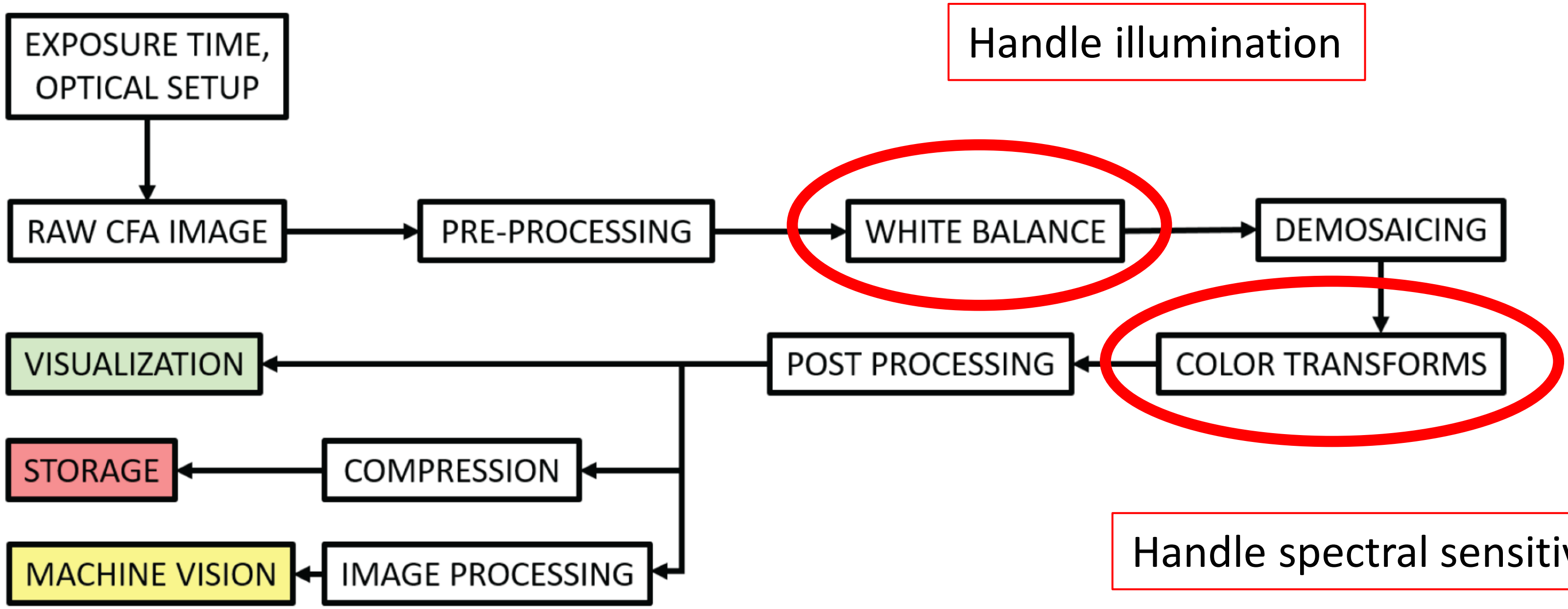
- Several spectral sensitivities but one space of representation



Relative similar representation

RGB





Handle illumination

Handle spectral sensitivities

Lapray, P.-J.; Thomas, J.-B.; Gouton, P. High Dynamic Range Spectral Imaging Pipeline For Multispectral Filter Array Cameras. *Sensors* **2017**, *17*, 1281. https://doi.org/10.3390/s17061281

A relative success!

- The impact of spectral properties can be limited

Abstract

It is an ill-posed problem to recover the true scene colors from a color biased image by discounting the effects of scene illuminant and camera spectral sensitivity (CSS) at the same time. Most color constancy (CC) models have been designed to first estimate the illuminant color, which is then removed from the color biased image to obtain an image taken under white light, without the explicit consideration of CSS effect on CC. This paper first studies the CSS effect on illuminant estimation arising in the inter-dataset-based CC (inter-CC), i.e., training a CC model on one dataset and then testing on another dataset captured by a distinct CSS. We show the clear degradation of existing CC models for inter-CC application. Then a simple way is proposed to overcome such degradation by first learning quickly a transform matrix between the two distinct CSSs (CSS-1 and CSS-2). The learned matrix is then used to convert the data (including the illuminant ground truth and the color-biased images) rendered under CSS-1 into CSS-2, and then train and apply the CC model on the color-biased images under CSS-2 without the need of burdensome acquiring of the training set under CSS-2. Extensive experiments on synthetic and real images show that our method can clearly improve the inter-CC performance for traditional CC algorithms. We suggest that, by taking the CSS effect into account, it is more likely to obtain the truly color constant images invariant to the changes of both illuminant and camera sensors.

Shao-Bing Gao, Ming Zhang, Chao-Yi Li, and Yong-Jie Li, "Improving color constancy by discounting the variation of camera spectral sensitivity,"
J. Opt. Soc. Am. A 34, 1448-1462 (2017)

Graham D. Finlayson, Mark S. Drew, and Brian V. Funt, "Spectral sharpening: sensor transformations for improved color constancy,"
J. Opt. Soc. Am. A 11, 1553-1563 (1994)

Spectral sharpening: sensor transformations for improved color constancy

Graham D. Finlayson, Mark S. Drew, and Brian V. Funt

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We develop sensor transformations, collectively called spectral sharpening, that convert a given set of sensor sensitivity functions into a new set that will improve the performance of any color-constancy algorithm that is based on an independent adjustment of the sensor response channels. Independent adjustment of multiplicative coefficients corresponds to the application of a diagonal-matrix transform (DMT) to the sensor response vector and is a common feature of many theories of color constancy, Land's retinex and von Kries adaptation in particular. We set forth three techniques for spectral sharpening. Sensor-based sharpening focuses on the production of new sensors as linear combinations of the given ones such that each new sensor has its spectral sensitivity concentrated as much as possible within a narrow band of wavelengths. Data-based sharpening, on the other hand, extracts new sensors by optimizing the ability of a DMT to account for a given illumination change by examining the sensor response vectors obtained from a set of surfaces under two different illuminants. Finally in perfect sharpening we demonstrate that, if illumination and surface reflectance are described by two- and three-parameter finite-dimensional models, there exists a unique optimal sharpening transform. All three sharpening methods yield similar results. When sharpened cone sensitivities are used as sensors, a DMT models illumination change extremely well. We present simulation results suggesting that in general nondiagonal transforms can do only marginally better. Our sharpening results correlate well with the psychophysical evidence of spectral sharpening in the human visual system.

Key words: spectral sharpening, color constancy, color balancing, lightness, von Kries adaptation.

A relative success!

- Applications seem to suffer little from the spectral differences

S. Bayram, H. Sencar, N. Memon and I. Avcibas, "Source camera identification based on CFA interpolation," *IEEE International Conference on Image Processing 2005*, 2005, pp. III-69, doi: 10.1109/ICIP.2005.1530330.

ABSTRACT

In this work, we focus our interest on blind source camera identification problem by extending our results in the direction of [1]. The interpolation in the color surface of an image due to the use of a color filter array (CFA) forms the basis of the paper. We propose to identify the source camera of an image based on traces of the proprietary interpolation algorithm deployed by a digital camera. For this purpose, a set of image characteristics are defined and then used in conjunction with a support vector machine based multi-class classifier to determine the originating digital camera. We also provide initial results on identifying source among two and three digital cameras.

Neural Network Generalization: The impact of camera parameters

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[2]State Key Laboratory of Automotive Simulation and Control, Jilin University

Corresponding author: Zhenyi Liu (e-mail: zhenyiliu27@gmail.com)

Supported by Jilin University. We thank Henryk Blasinski for his contributions.

ABSTRACT We quantify the generalization of a convolutional neural network (CNN) trained to identify cars. First, we perform a series of experiments to train the network using one image dataset - either synthetic or from a camera - and then test on a different image dataset. We show that generalization between images obtained with different cameras is roughly the same as generalization between images from a camera and ray-traced multispectral synthetic images. Second, we use ISETAuto, a soft prototyping tool that creates ray-traced multispectral simulations of camera images, to simulate sensor images with a range of pixel sizes, color filters, acquisition and post-acquisition processing. These experiments reveal how variations in specific camera parameters and image processing operations impact CNN generalization. We find that (a) pixel size impacts generalization, (b) demosaicking substantially impacts performance and generalization for shallow (8-bit) bit-depths but not deeper ones (10-bit), and (c) the network performs well using raw (not demosaicked) sensor data for 10-bit pixels.

Z. Liu, T. Lian, J. Farrell and B. A. Wandell, "Neural Network Generalization: The Impact of Camera Parameters," in *IEEE Access*, vol. 8, pp. 10443-10454, 2020, doi: 10.1109/ACCESS.2020.2965089.

(Although metamerism difference could be used as a camera fingerprint)

How is this addressed in Spectral imaging?

- Calibration (spectral reconstruction)
  - Equivalent to a colour transform

$$\mathbf{f} = \int_{\omega} e(\lambda) r(\lambda) \mathbf{c}(\lambda) \mathrm{d}\lambda$$

E. M. Valero, J. L. Nieves, S. M. C. Nascimento, K. Amano, and D. H. Foster, "Recovering spectral data from natural scenes with an RGB digital camera and colored filters," Color. Res. & Appl. 32, 352–360 (2007).

L. T. Maloney, "Evaluation of linear models of surface spectral reflectance with small numbers of parameters," J. Opt. Soc. Am. A 3, 1673–1683 (1986).

- Illumination (spectral constancy)
  - Equivalent to white balance

$$\mathbf{f} = \int_{\omega} e(\lambda) r(\lambda) \mathbf{c}(\lambda) \mathrm{d}\lambda$$

Haris Ahmad Khan, Jean-baptiste Thomas, Jon Yngve Hardeberg, Olivier Laligant, "Spectral Adaptation Transform for Multispectral Constancy" in *Journal of Imaging Science and Technology*, 2018, pp 20504-1 - 20504-12, https://doi.org/10.2352/J.ImagingSci.Technol.2018.62.2.020504

Haris Ahmad Khan, Jean-Baptiste Thomas, Jon Yngve Hardeberg, and Olivier Laligant, "Multispectral camera as spatio-spectrophotometer under uncontrolled illumination," Opt. Express 27, 1051-1070 (2019)

- File format (CIE 223:2017)

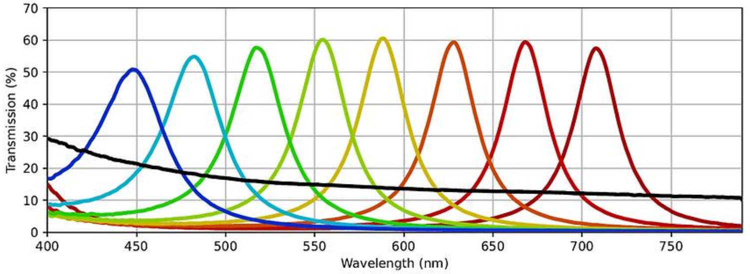
MULTISPECTRAL IMAGE FORMATS, CIE 223:2017, Division 8
ISBN: 978-3-902842-10-7

This technical report describes the basic model of multispectral imaging technology followed by the requirements and the examples of multispectral image formats suitable for colour imaging applications. Four example formats are introduced and compared in typical use cases: JPEG 2000, Spectral Binary File Format, Natural Vision, and multispectral image file format AIX. The specifications of those formats except for JPEG 2000 are provided in the Annex.

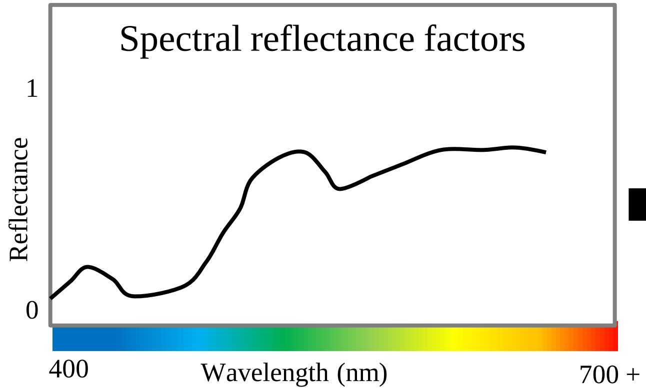
Wish list for a conceptual target space

- Compact data (reduced dimension, easy to transfer)
- Practical (direct visualisation, easy to interact)
- Handling non visible parts (NIR)
- Conceptually relevant in a large sense (?)
- Generally accepted and standardised

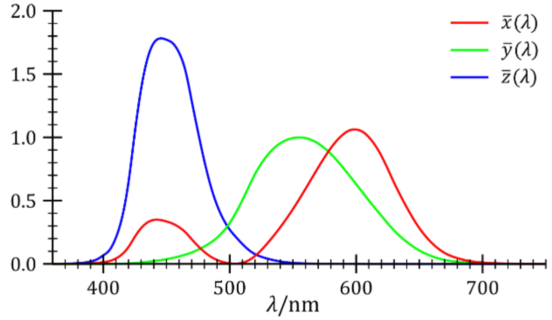
De facto spaces: reflectance factors and tristimulus values

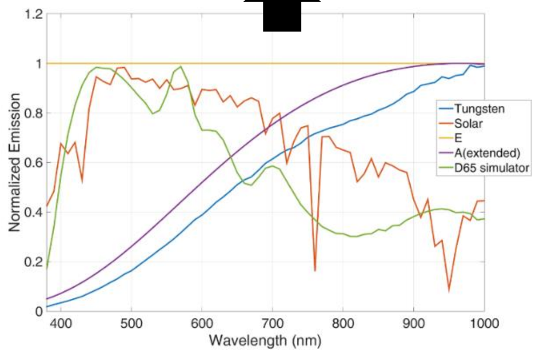


$$\mathbf{f} = \int_{\omega} e(\lambda) r(\lambda) \mathbf{c}(\lambda) \mathrm{d}\lambda$$



https://commons.wikimedia.org/wiki/File:CIE_1931_XYZ_Color_Matching_Functions.svg





XYZ

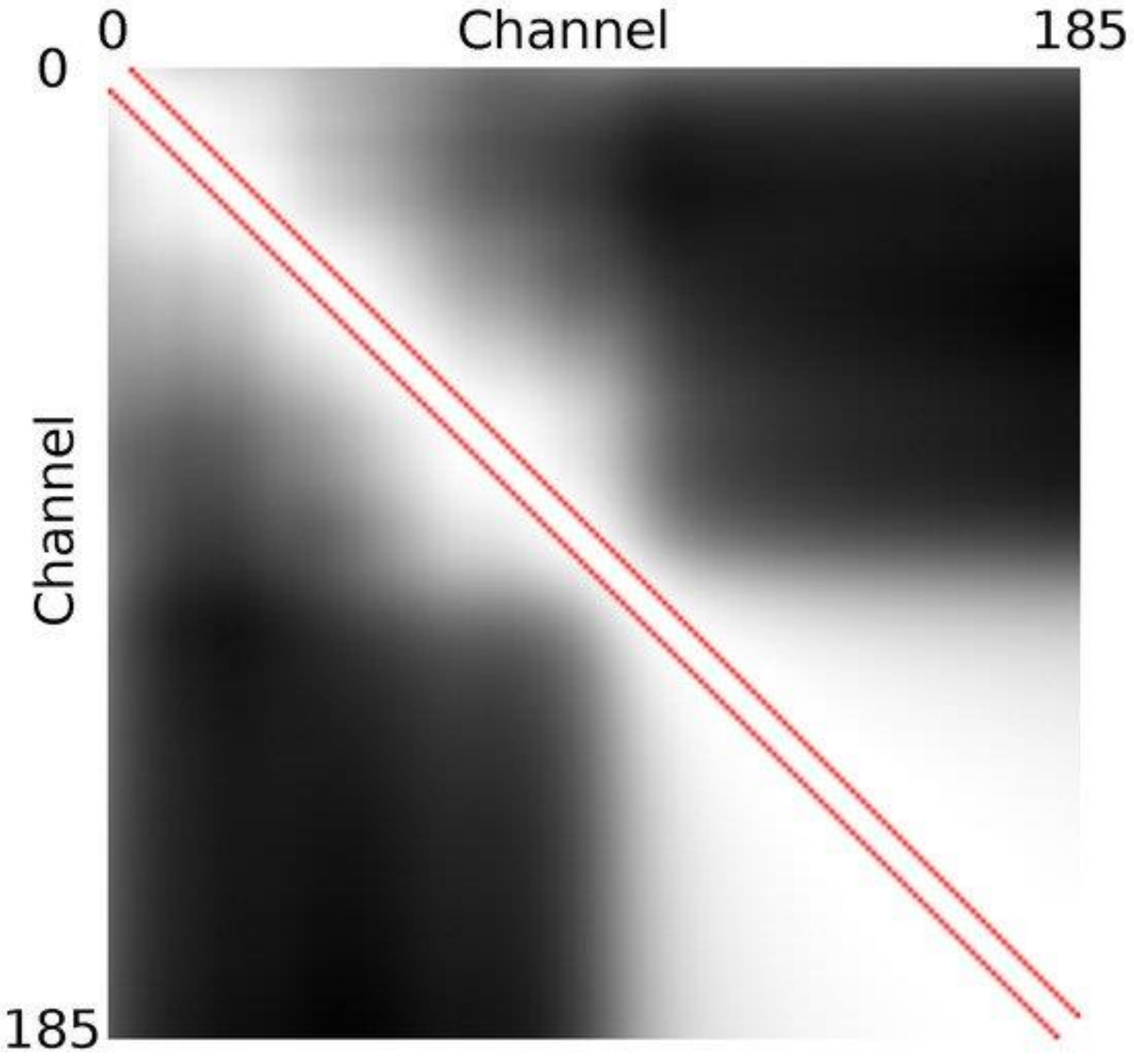
- SRF: Compactness?
- XYZ: Loss? Quid of NIR?
- Fast and interactive spectral and colorimetric visualisation possible

Colantoni, P., Thomas, JB. (2009). A Color Management Process for Real Time Color Reconstruction of Multispectral Images. In: Salberg, AB., Hardeberg, J.Y., Jenssen, R. (eds) Image Analysis. SCIA 2009. Lecture Notes in Computer Science, vol 5575. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-02230-2_14

Colantoni P, Thomas J-B, Hébert M, Caissard J-C and Trémeau A (2022), "Web-Based Interaction and Visualization of Spectral Reflectance Images: Application to Vegetation Inspection", SN Computer Science. Vol. 3, pp. 12.

Spectral correlations and NIR

- Little correlation between VIS and NIR
- High correlation between neighboring bands
- High correlation in the NIR part
  - Until 1000 nm
  - Only on a reduce set of material (textiles)



Normalized covariance between each couple of channels over the Hytexila dataset. Values range between 31% (black) and 100% (white). The two red lines are separated by seven channels, and inside the red lines, the covariance is above 95%.

Khan, H.A.; Mihoubi, S.; Mathon, B.; Thomas, J.-B.; Hardeberg, J.Y. HyTexiLa: High Resolution Visible and Near Infrared Hyperspectral Texture Images. *Sensors* **2018**, *18*, 2045. https://doi.org/10.3390/s18072045

Partial answer: Information based representations

- PCA or equivalent
  - Dimensions to keep?
  - Definition of an effective dimension
  - Do we loose the advantage?
- Includes NIR
- No intuitive direct visualisation

Hardeberg, J.Y. On the Spectral Dimensionality of Object Colours. In *Conference on Colour in Graphics, Imaging, and Vision*; Society for Imaging Science and Technology: Springfield, VA, USA, 2002; pp. 480–485

- Better to use non-negative matrix factorization?

Berry, M.W.; Browne, M.; Langville, A.N.; Pauca, V.P.; Plemmons, R.J. Algorithms and applications for approximate nonnegative matrix factorization. *Comput. Stat. Data Anal.* **2007**, *52*, 155–173.

- Basis functions (Fourier, wavelets)

J. Jia, K. J. Barn, Waveletard and K. Hirakawa, "Fourier Spectral Filter Array for Optimal Multispectral Imaging," in *IEEE Transactions on Image Processing*, vol. 25, no. 4, pp. 1530-1543, April 2016.

Partial answer: LabPQR -> RGB-PQR-NIR

- Direct colour visualisation from the first 3 bands
- Effective dimension?
- Redundancy between Color and PQR
- Quid of NIR?

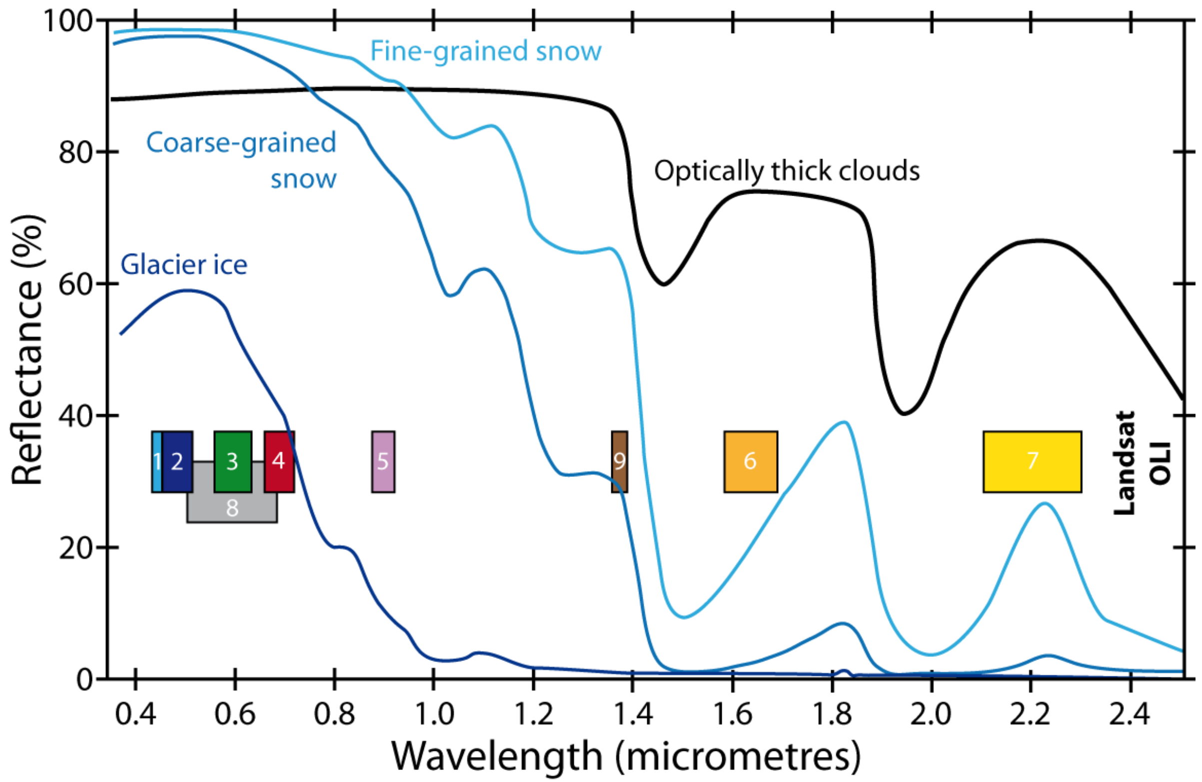
Derhak, M., Rosen, M.: Spectral colorimetry using LabPQR: An interim connection space. Journal of Imaging Science and Technology 50(1), 53–63 (2006)

Fairchild, M.D., Johnson, G.M.: METACOW: A public-domain, high-resolution, fully-digital, noise-free, metameric, extended-dynamic-range, spectral test target for imaging system analysis and simulation. CIC 2004. pp. 239-245.

Thomas J-B and Hardeberg JY (2020), *"How to Look at Spectral Images? A Tentative Use of Metameric Black for Spectral Image Visualisation"*, In Colour and Visual Computing Symposium 2020. Aachen (2688), pp. 1-11.

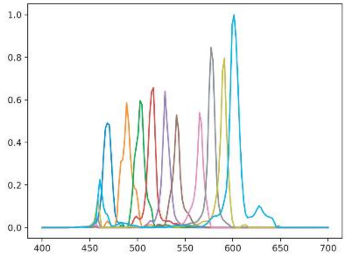
Partial answer: Landsat 8 OLI, etc.

- Fields standardised spectral imaging products, e.g. remote sensing



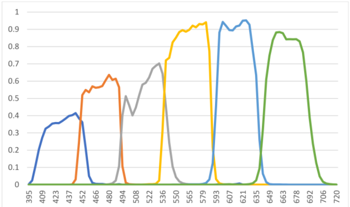
Colin Prieur, Antoine Rabatel, Jean-Baptiste Thomas, Ivar Farup, Jocelyn Chanussot, Machine learning approaches to automatically detect glacier snow lines on multi-spectral satellite images, To appear.

Summary



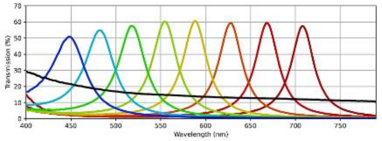
XiSpec, CorXimea

→ Imaging pipeline Codec cam 1



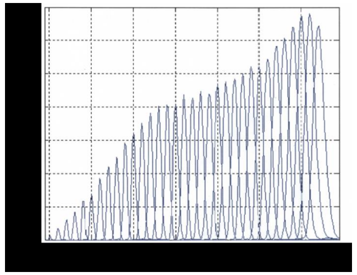
Pixelteq Spectrocam™

→ Imaging pipeline Codec cam 2



SILIOS, CMS-C

→ Imaging pipeline Codec cam 3



VariSpec LCTF filters

→ Imaging pipeline Codec cam 4

→ Spectral Data Representation Space → Processing

Conclusion

Main take away: Reflectance factor **may** not be
the best common standard space
to encode spectral images

Should we think about it?

CIE Div.8 RF01, spectral imaging -> Technical Committee?

Standardization of spectral imaging:
What is the RGB of spectral images?

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Spektralion AS