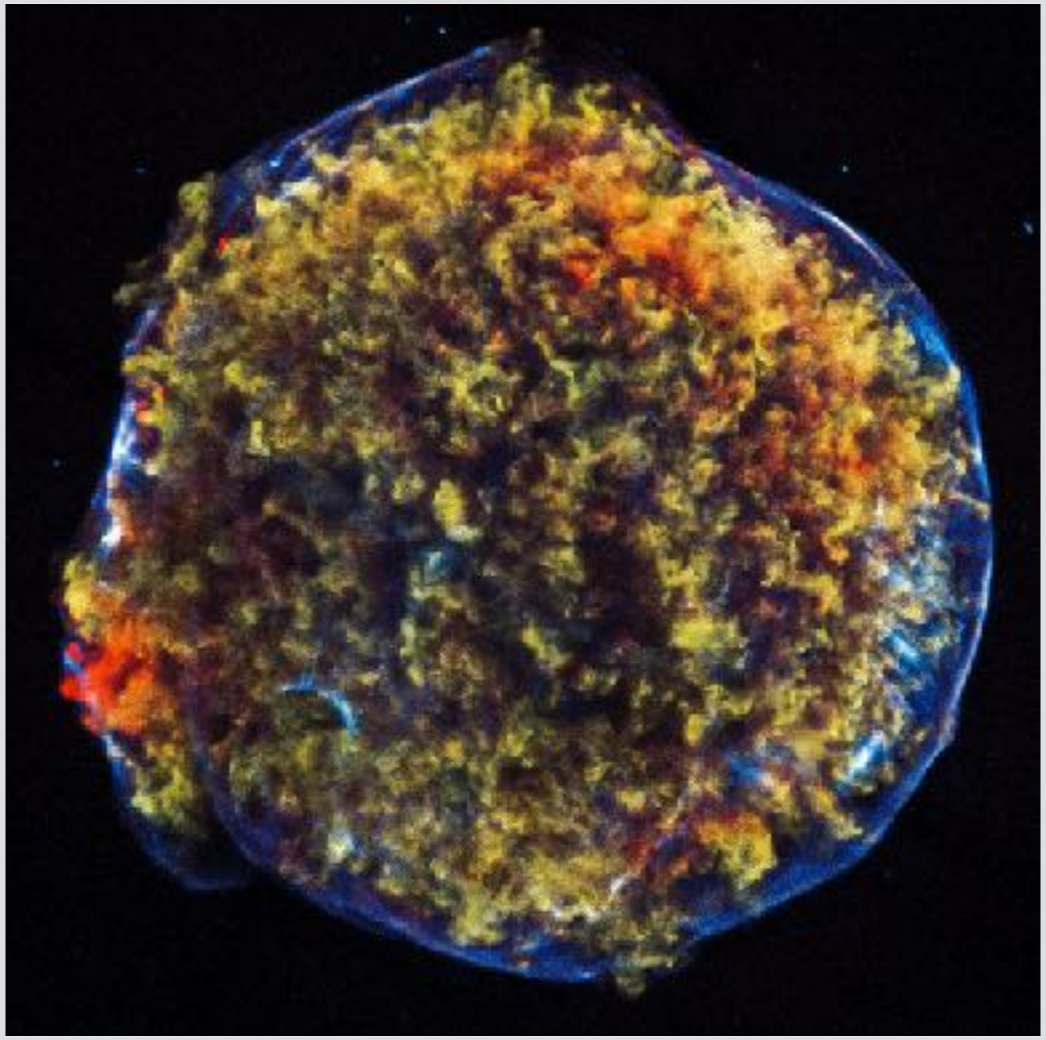
Revisiting the ejecta asymmetries in Cassiopeia A with a novel method for component separation in X-ray astronomy



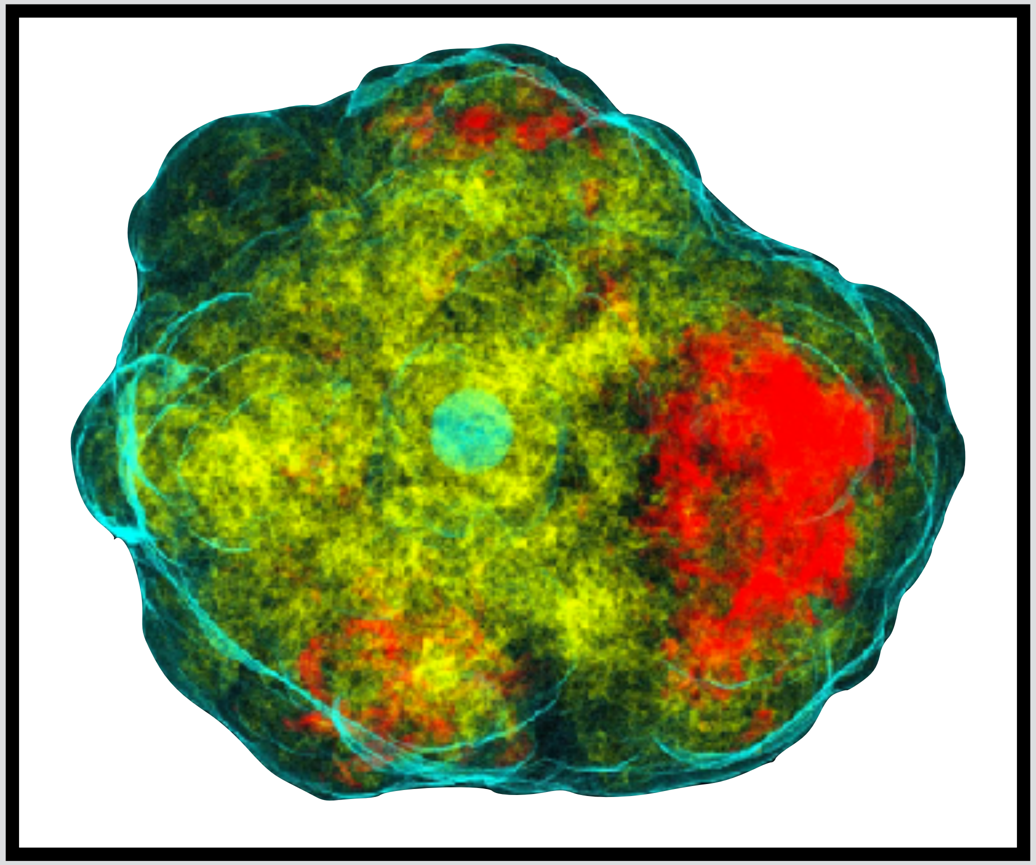
Adrien Picquenot

Fabio Acero Jérôme Bobin

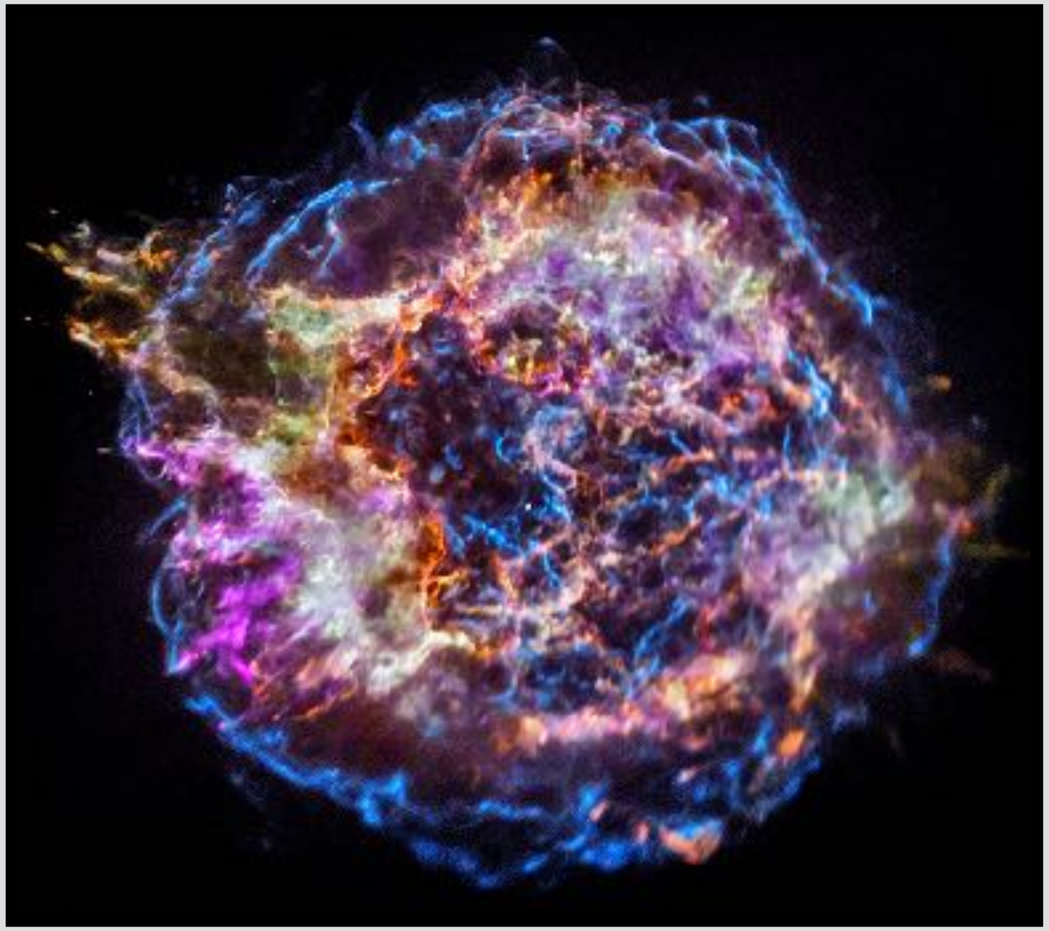
Summary

- Supernova remnants in X-rays
- Traditional analysis methods of spectro-imaging instruments
- An introduction to the Generalyzed Morphological Components Analysis
- Benchmarking the method with SNR Cassiopeia A Toy models
- Application to real data of Cassiopeia A

Core Collapse Supernovas



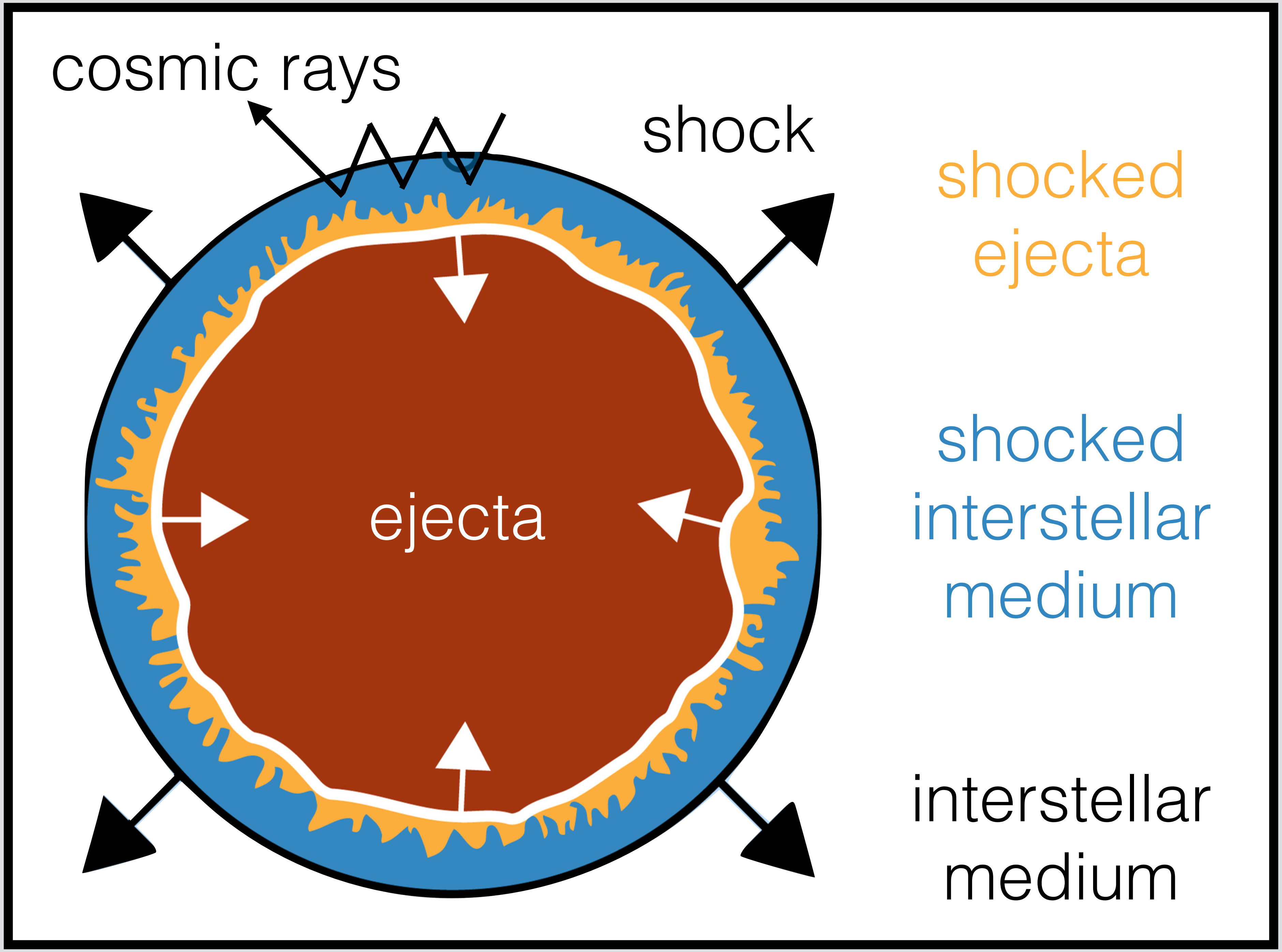
Simulation, SXS project



Cassiopeia A seen by *Chandra*

Asymmetries in the explosion proved necessary in the simulations.

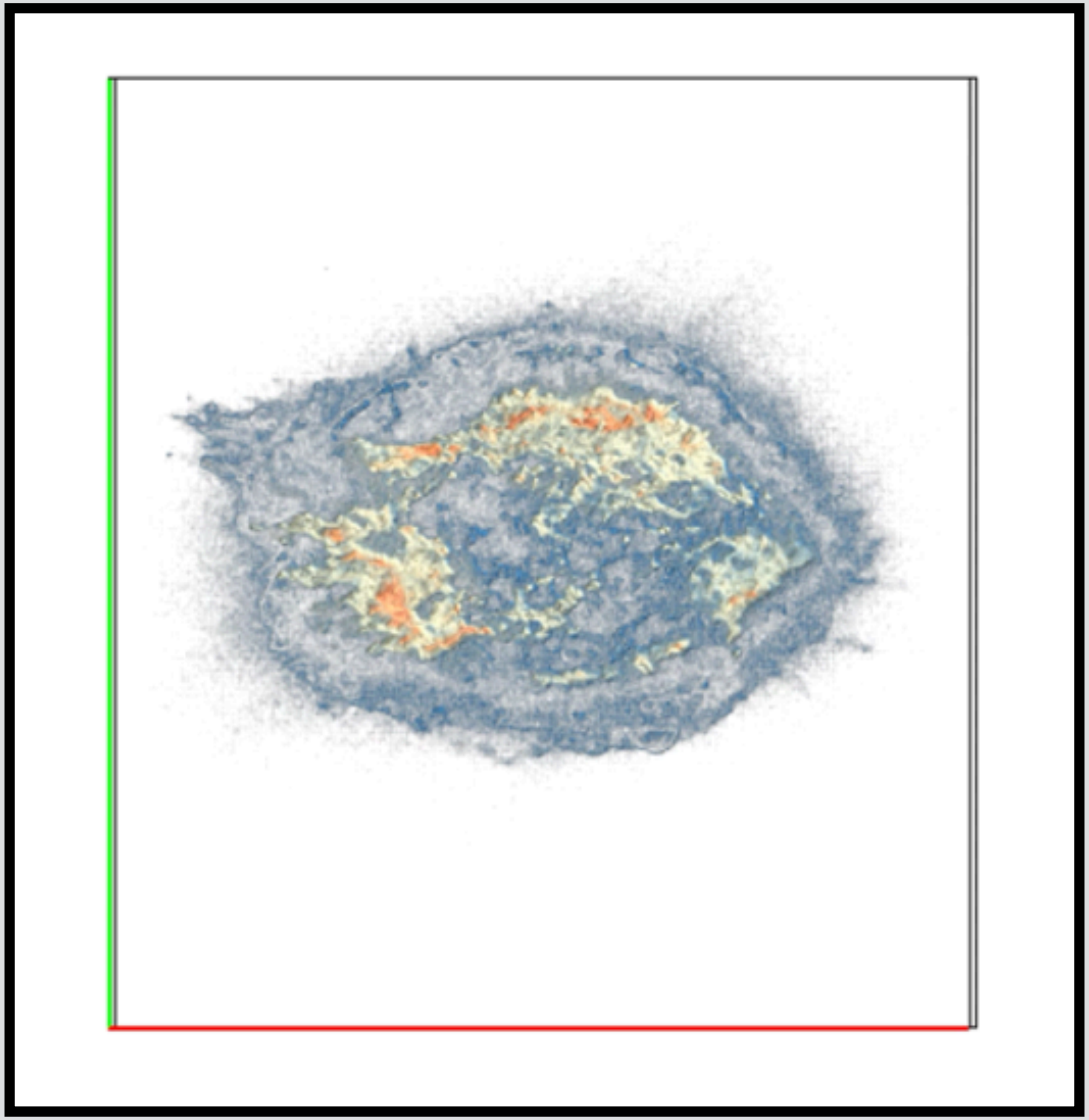
Supernova Remnants



Ejecta can trace the explosion mechanisms.

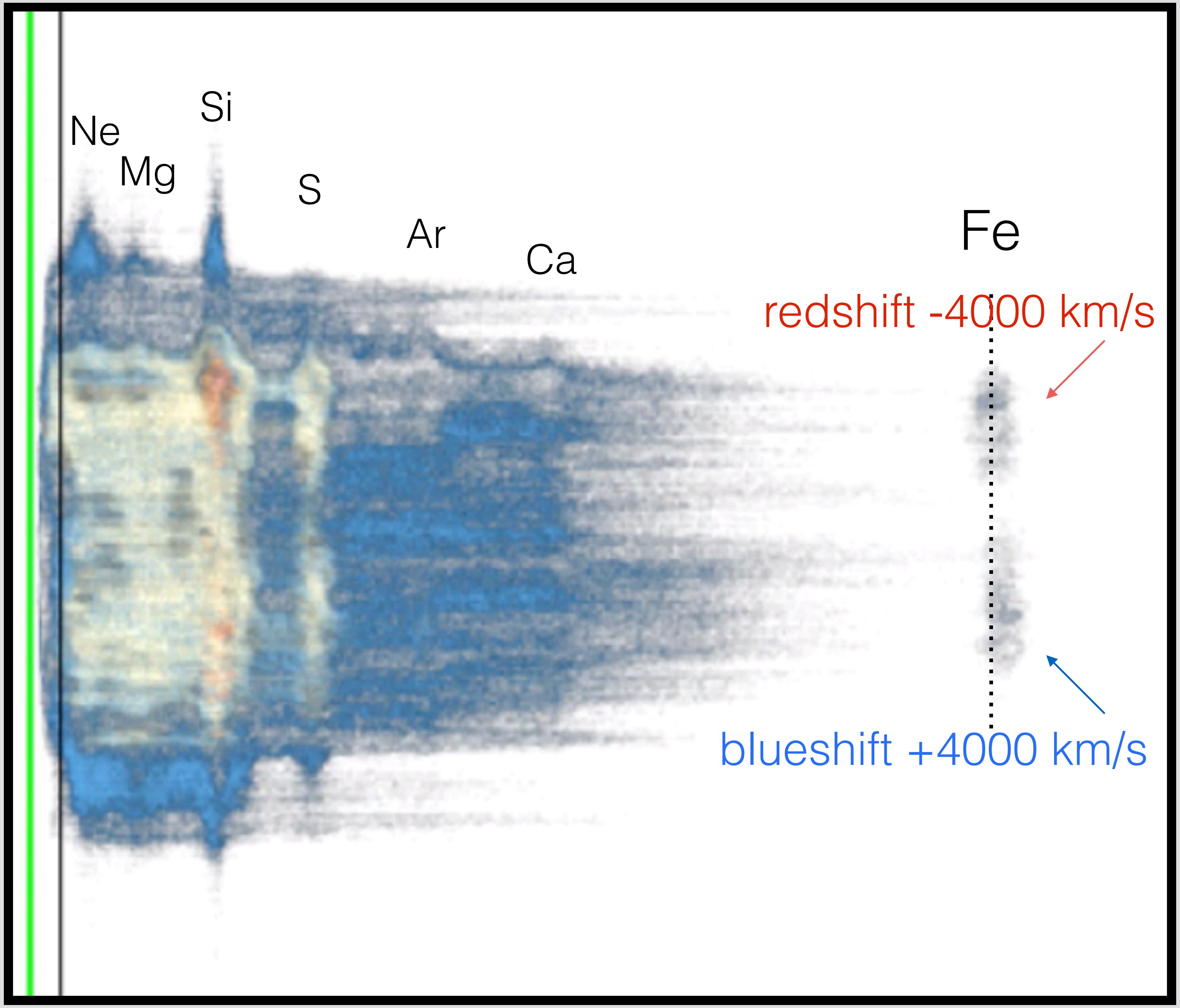
Supernova Remnants in X-rays

Cassiopeia A data cube (x,y,E)

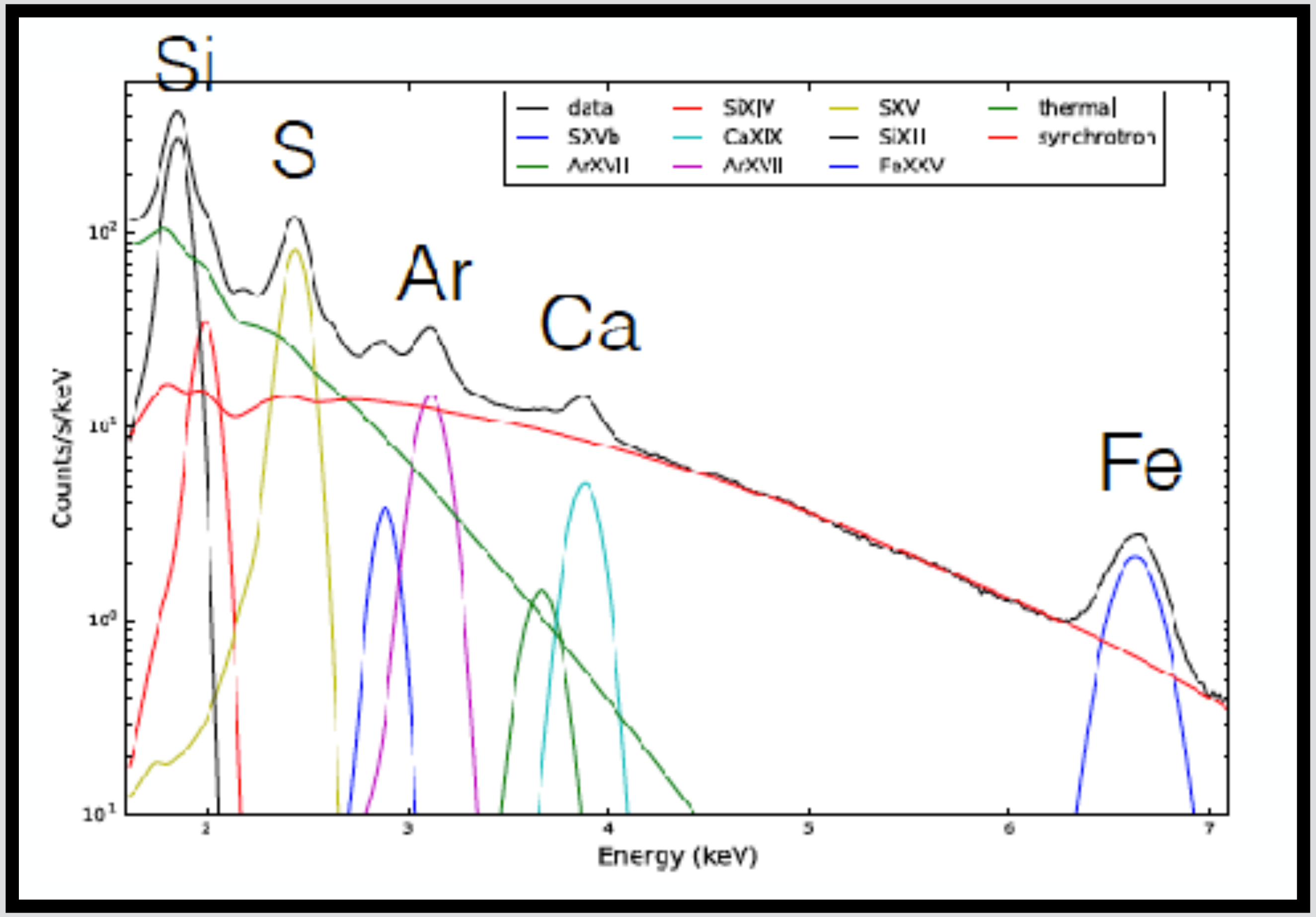


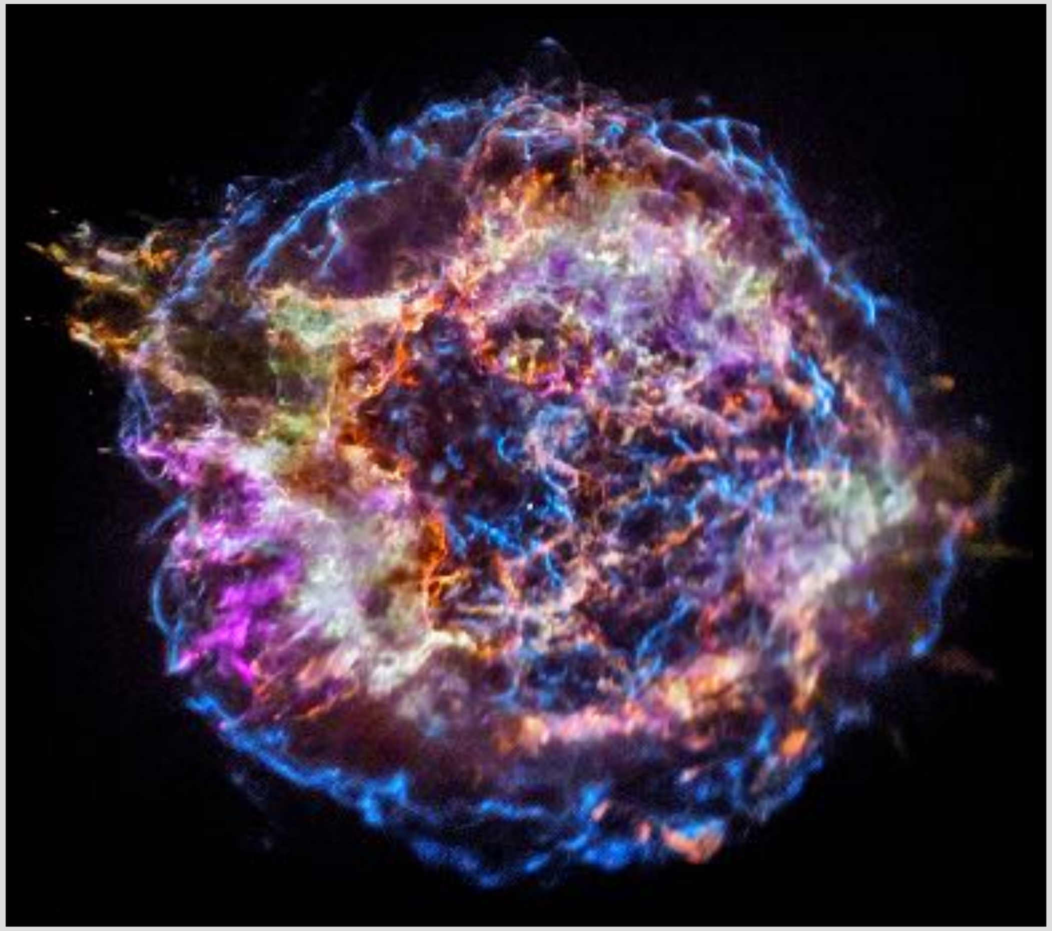
Chandra data, visualized with vaex

Supernova Remnants in X-rays



Supernova Remnants in X-rays

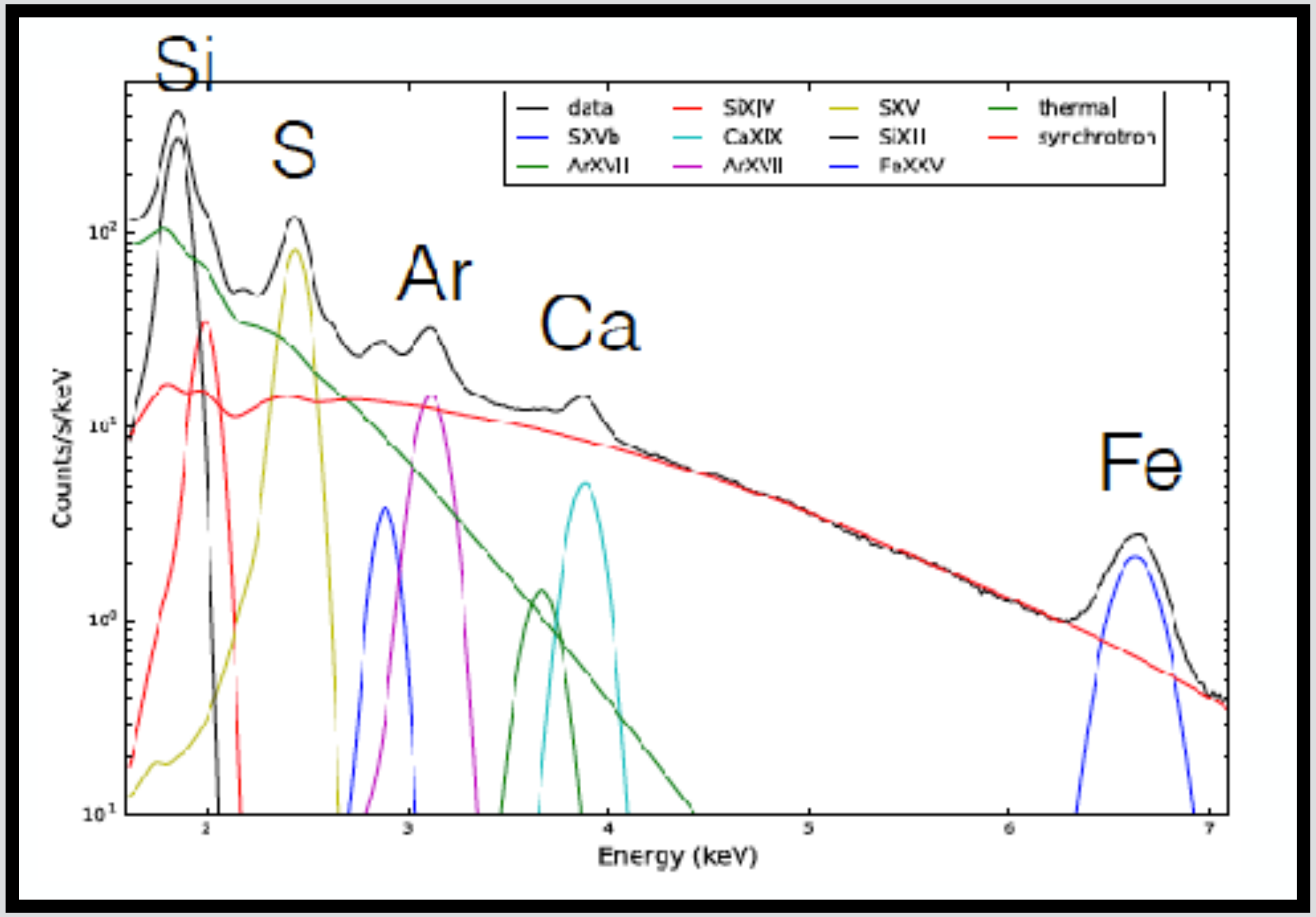


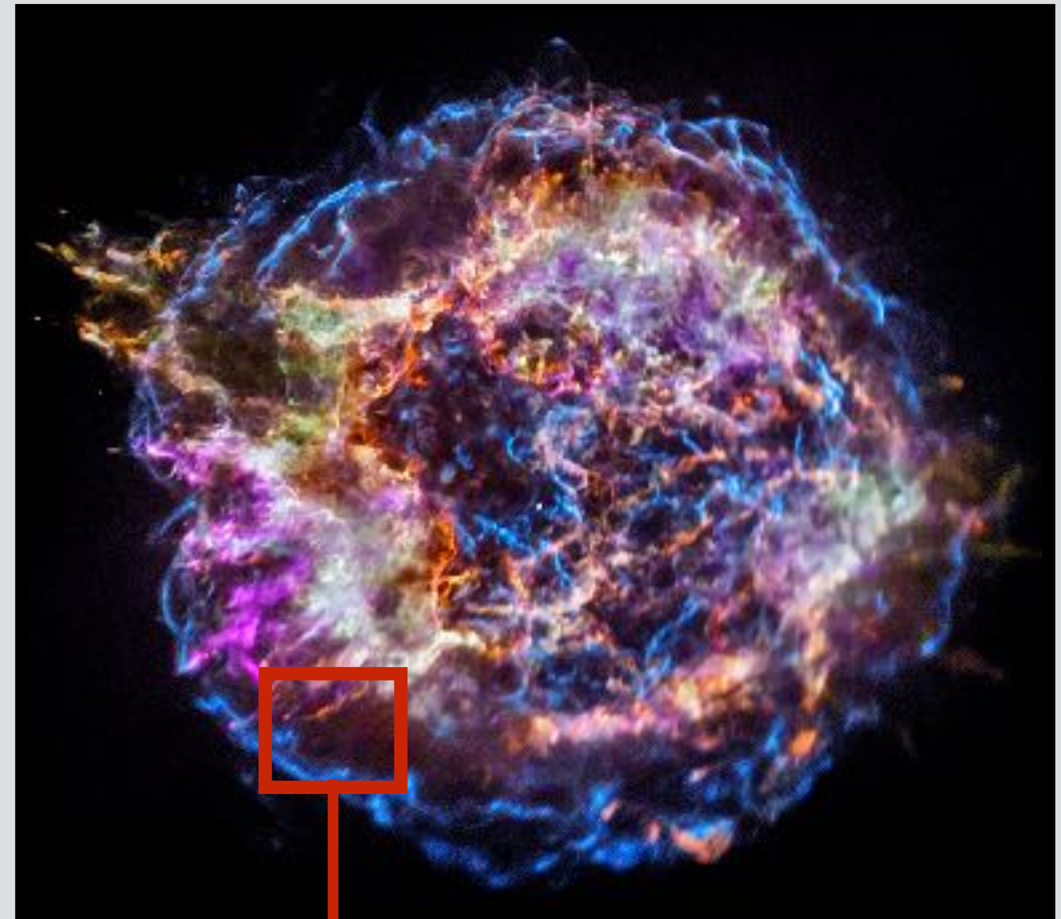


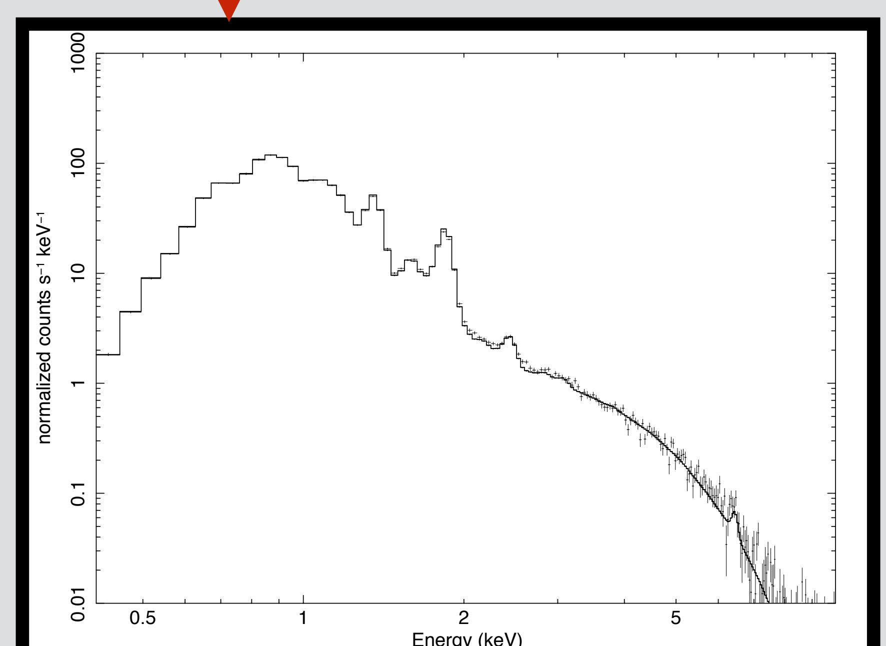
- Thermal emission continuum
- Synchrotron emission continuum
- Line emissions

How to obtain a clear image of those components ?

Traditional Analysis Methods

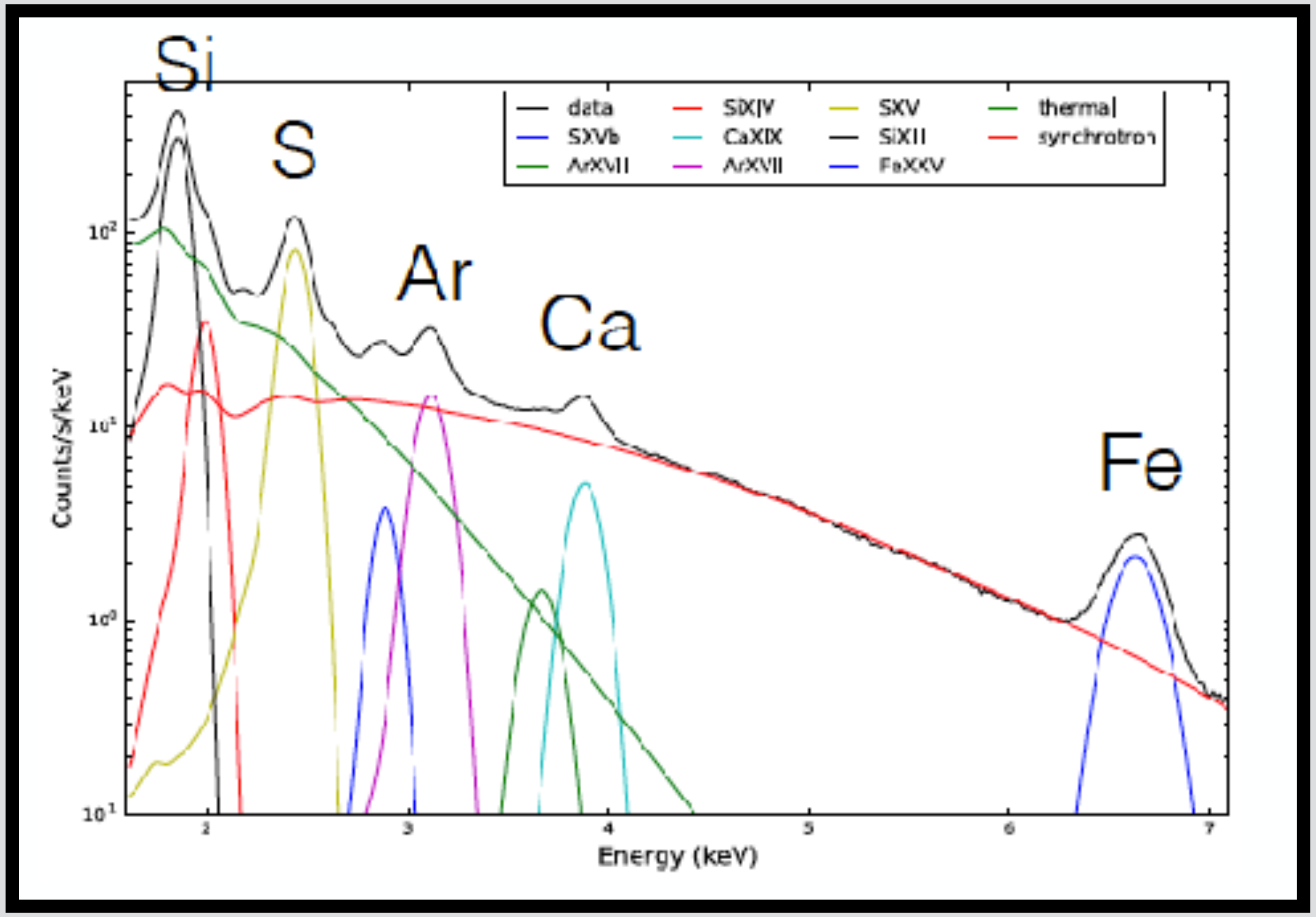


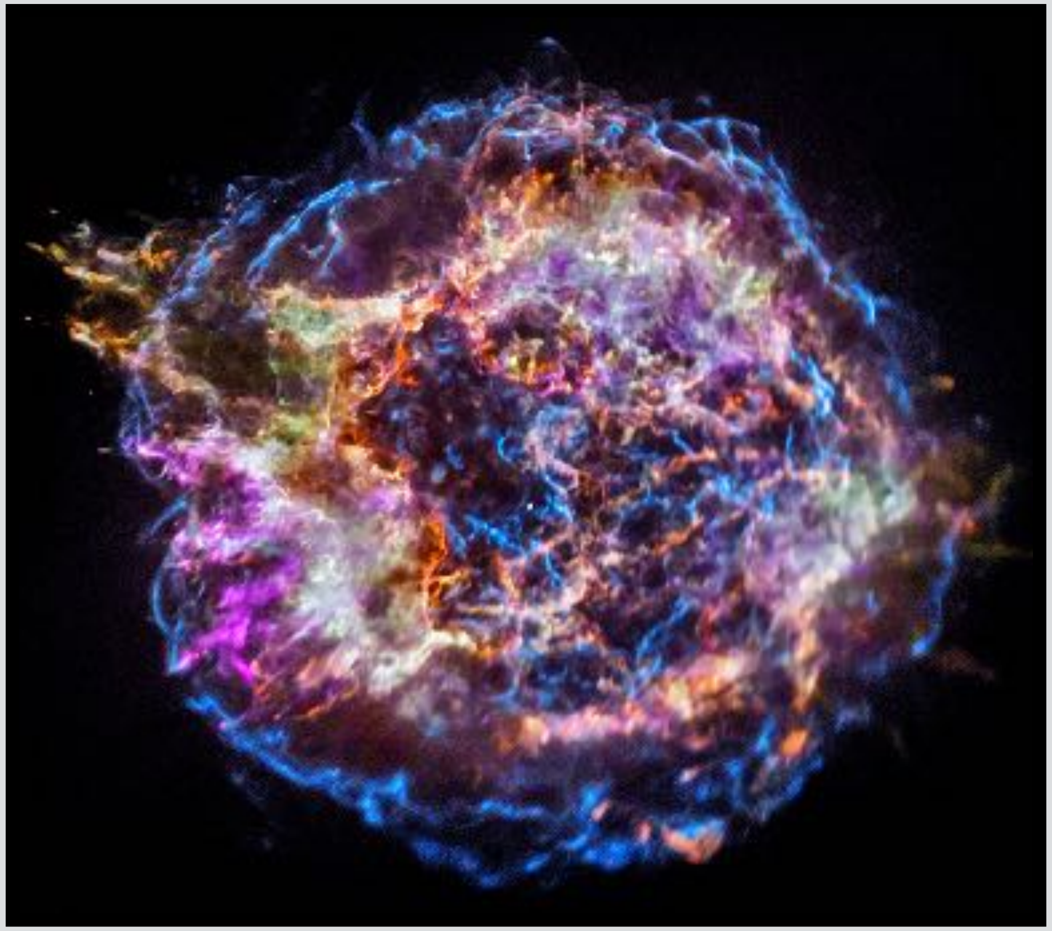


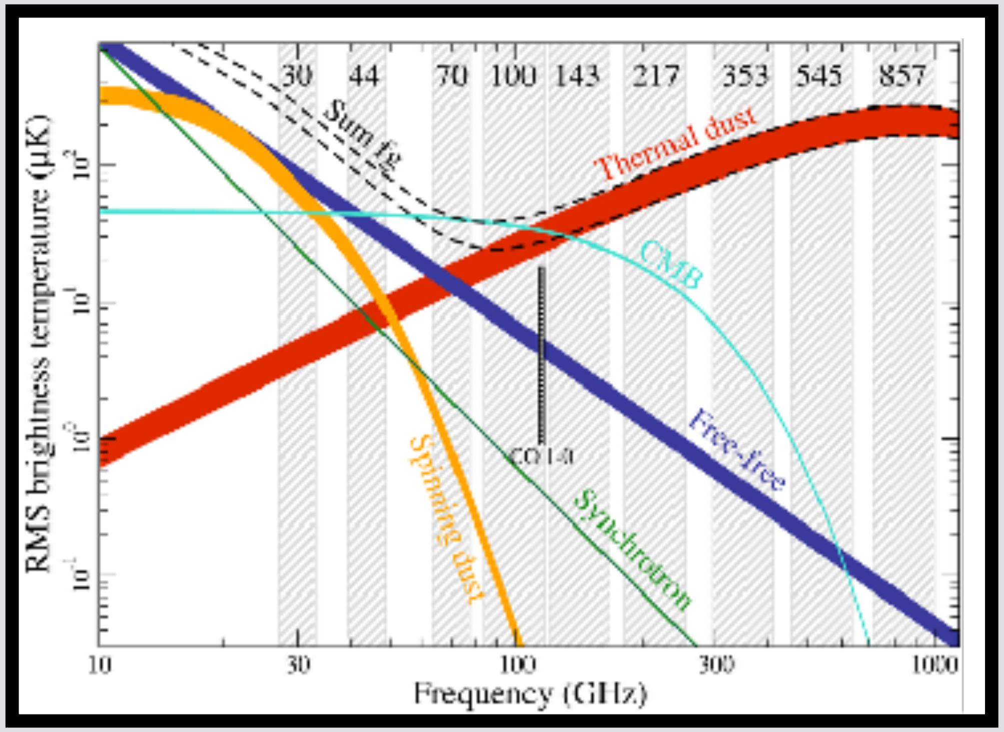


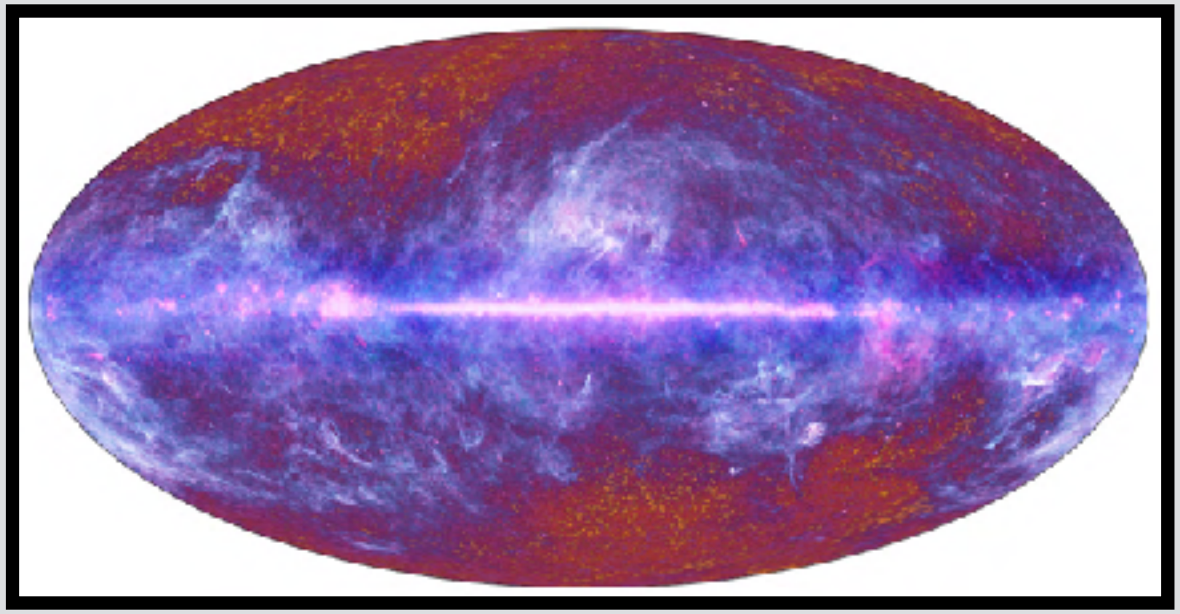
Decomposition is made on the spectra retrieved from particular places defined on the images, without leveraging Chandra's great spatial resolution.

Analogy with the CMB









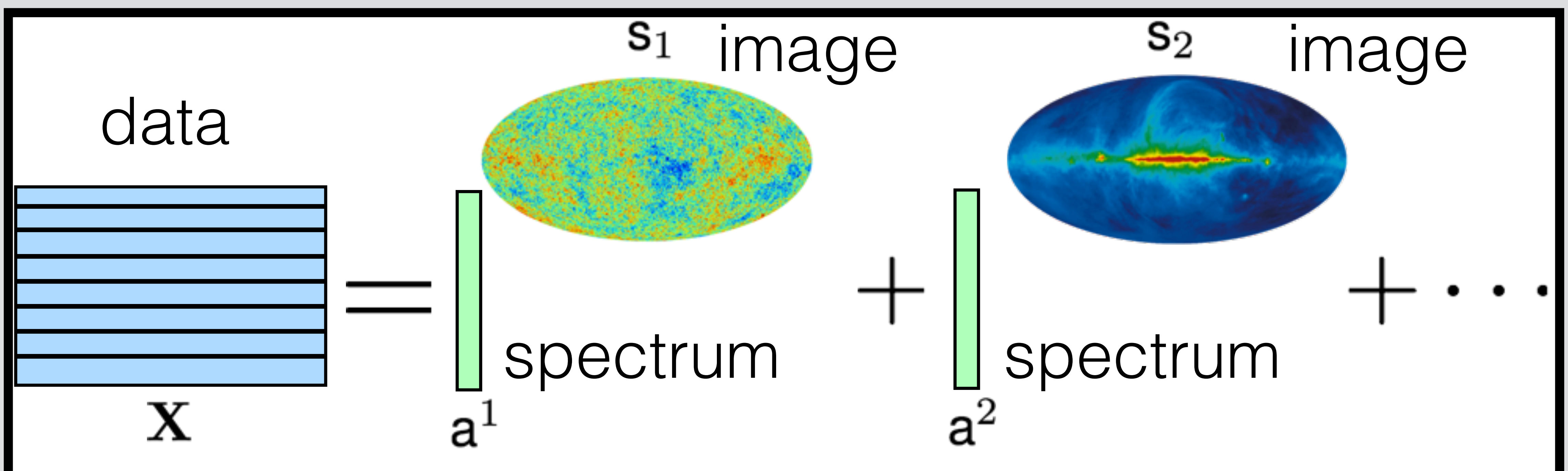
Planck survey of the sky

GMCA

Generalized Morphological Components Analysis (Bobin et al. 2016)

$$X = AS + N = \sum_{i=1}^{n} A_i S_i + N$$

Blind Source Separation algorithm : The aim is to retrieve n images (x,y) and spectra (E) from the initial (E,x,y) data set without prior instrumental or physical knowledge.



GMCA

$$X = AS + N = \sum_{i=1}^{n} A_i S_i + N$$

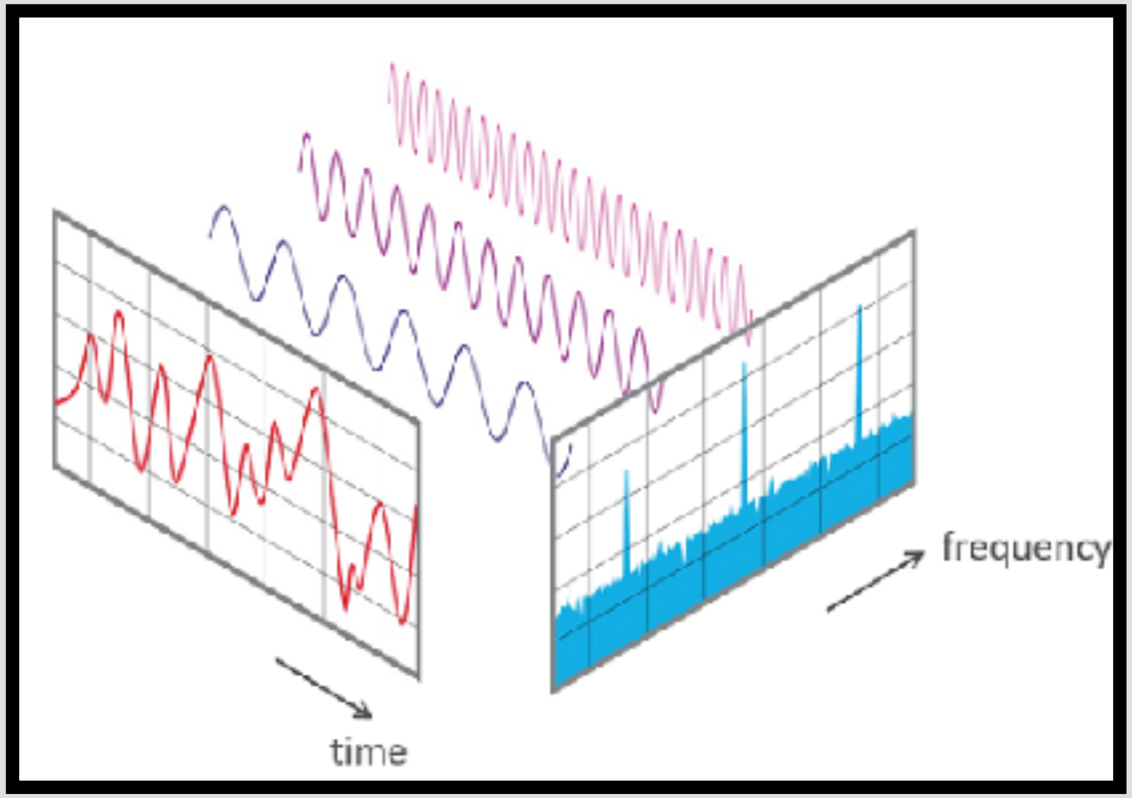
Without any information on A and S,
this problem is ill-posed.

$$\min_{A,S} \|X - AS\|_F^2$$

How can we add a constraint that will help disentangling?

The concept of sparsity

Analogy with 1-D :



The Fourrier transform allows to describe periodic signals with only a few non zero coefficients.

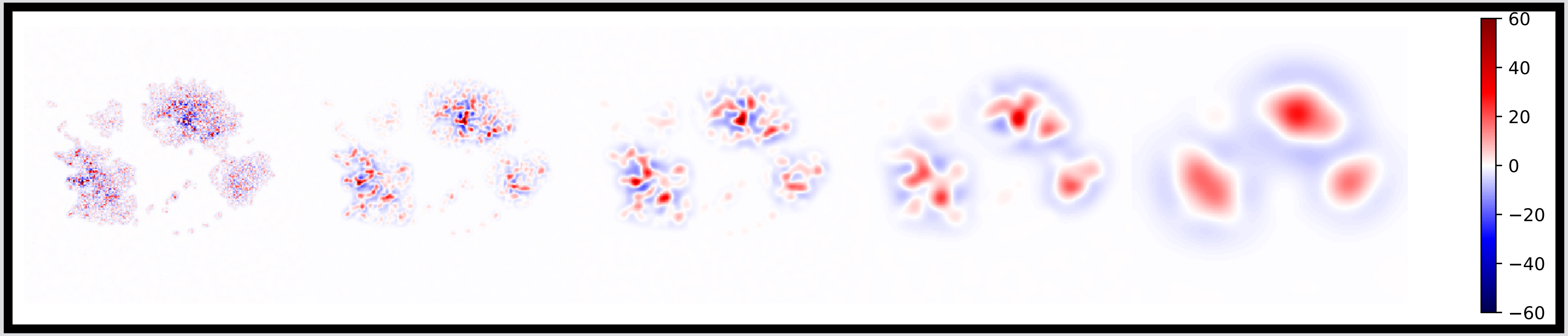
It makes the different components easier to disentangle by diminishing the overlapping.

The concept of sparsity

In 2-D :

Wavelet transforms give sparse representations of images. In particular, *Starlets* are well adapted for astrophysical images.

Small scales Large scales

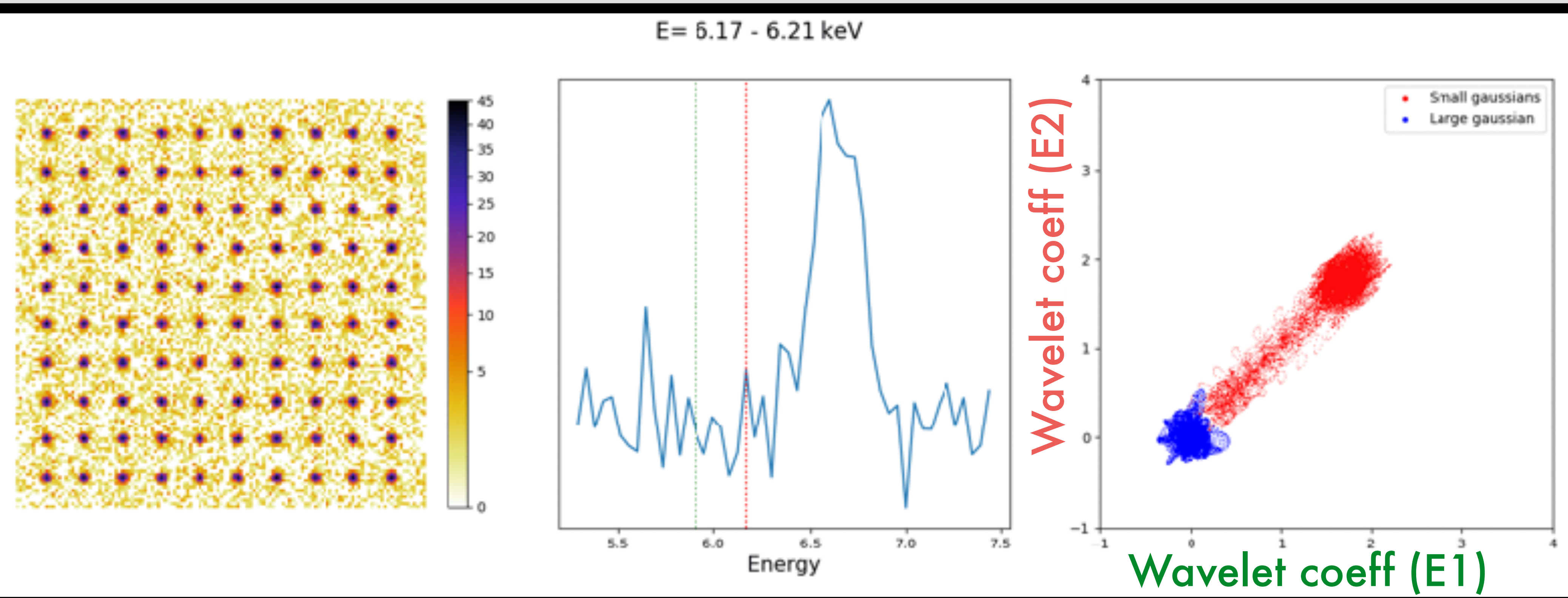


Starlet transform of the Fe structure in Cassiopeia A

GMCA

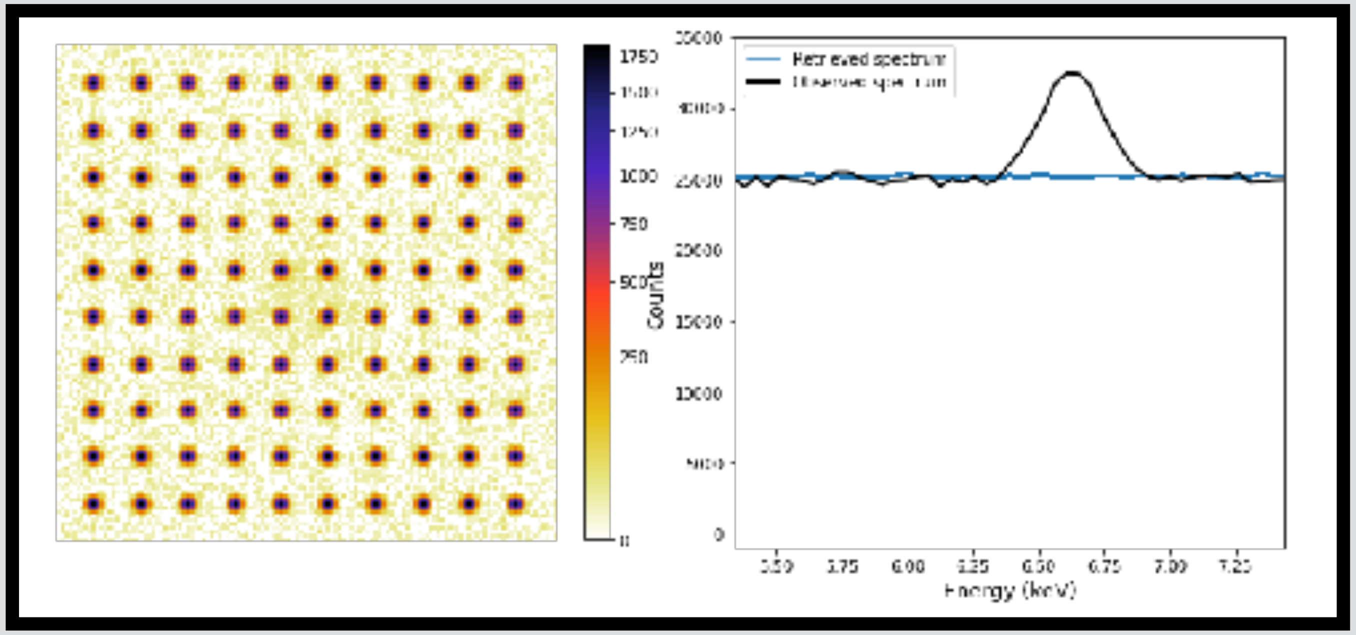
The concept of sparsity

In 2-D :

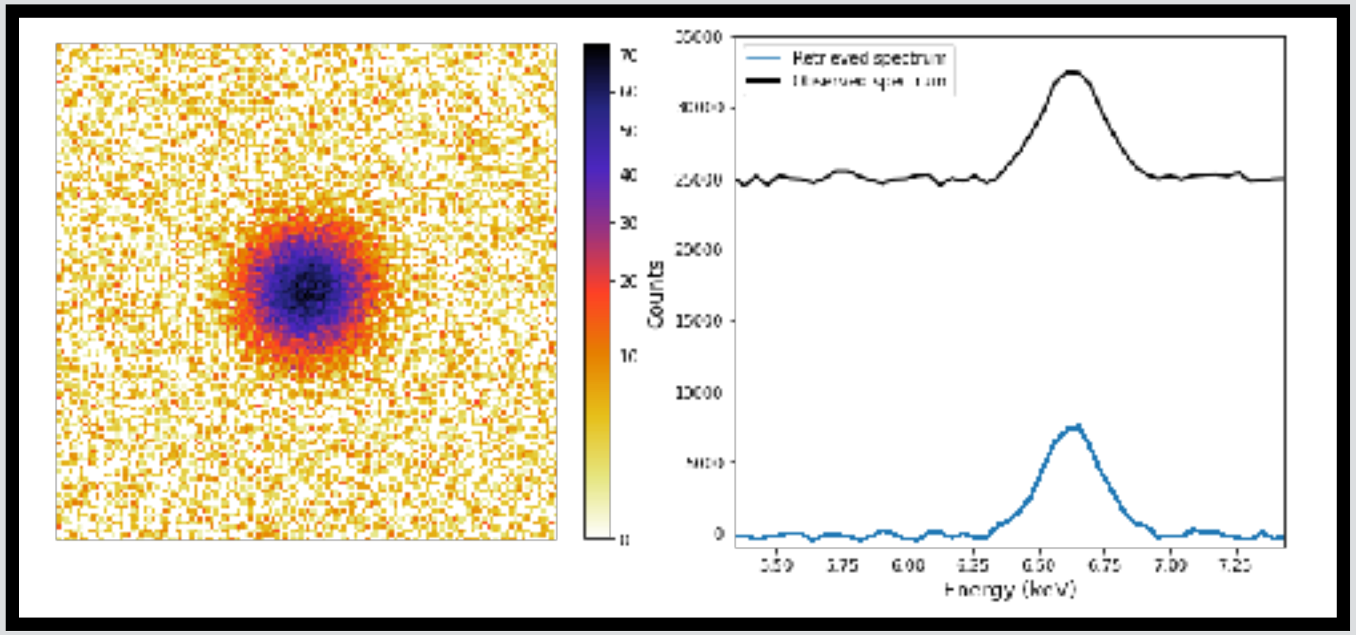


Starlet transform third scale coefficients of gaussians of different sizes

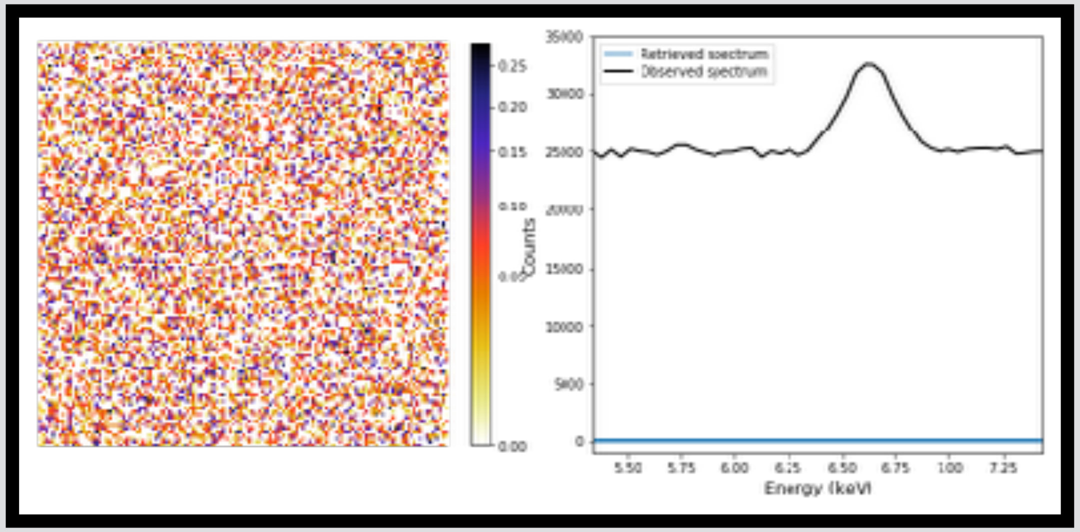
GMCA



A grid of small gaussians with a constant spectrum



A large gaussian with a gaussian spectrum



Noise

GMCA

$$X = AS + N = \sum_{i=1}^{n} A_i S_i + N$$

Without any information on A and S,
this problem is ill-posed.

$$\min_{A,S} \| X - AS \|_F^2$$

GMCA

$$X = AS + N = \sum_{i=1}^{n} A_i S_i + N$$

With a sparsity constraint term :

$$\min_{A,S} \sum_{i=1}^{n} \lambda_i \|S_i\|_p + \|X - AS\|_F^2$$

GMCA

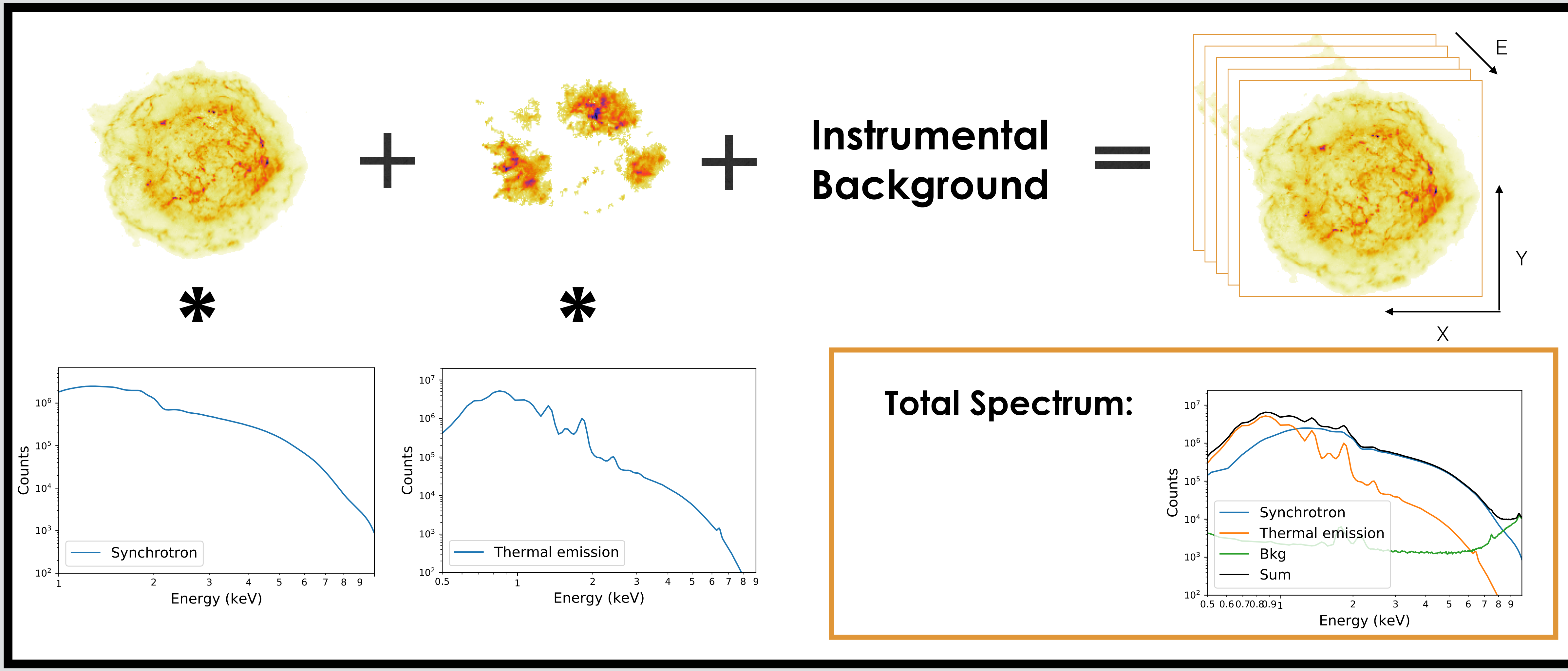
$$\min_{A,S} \sum_{i=1}^{n} \lambda_i \|S_i\|_p + \|X - AS\|_F^2$$

The algorithm is iterative, each iteration containing two steps :

- Step 1: Estimation of S for fixed A, by simultaneously minimizing $\|X - AS\|_F$ and the term enforcing sparsity in the Wavelet domain;
- Step 2: Estimation of A for fixed S by minimizing $\|X - AS\|_F$.

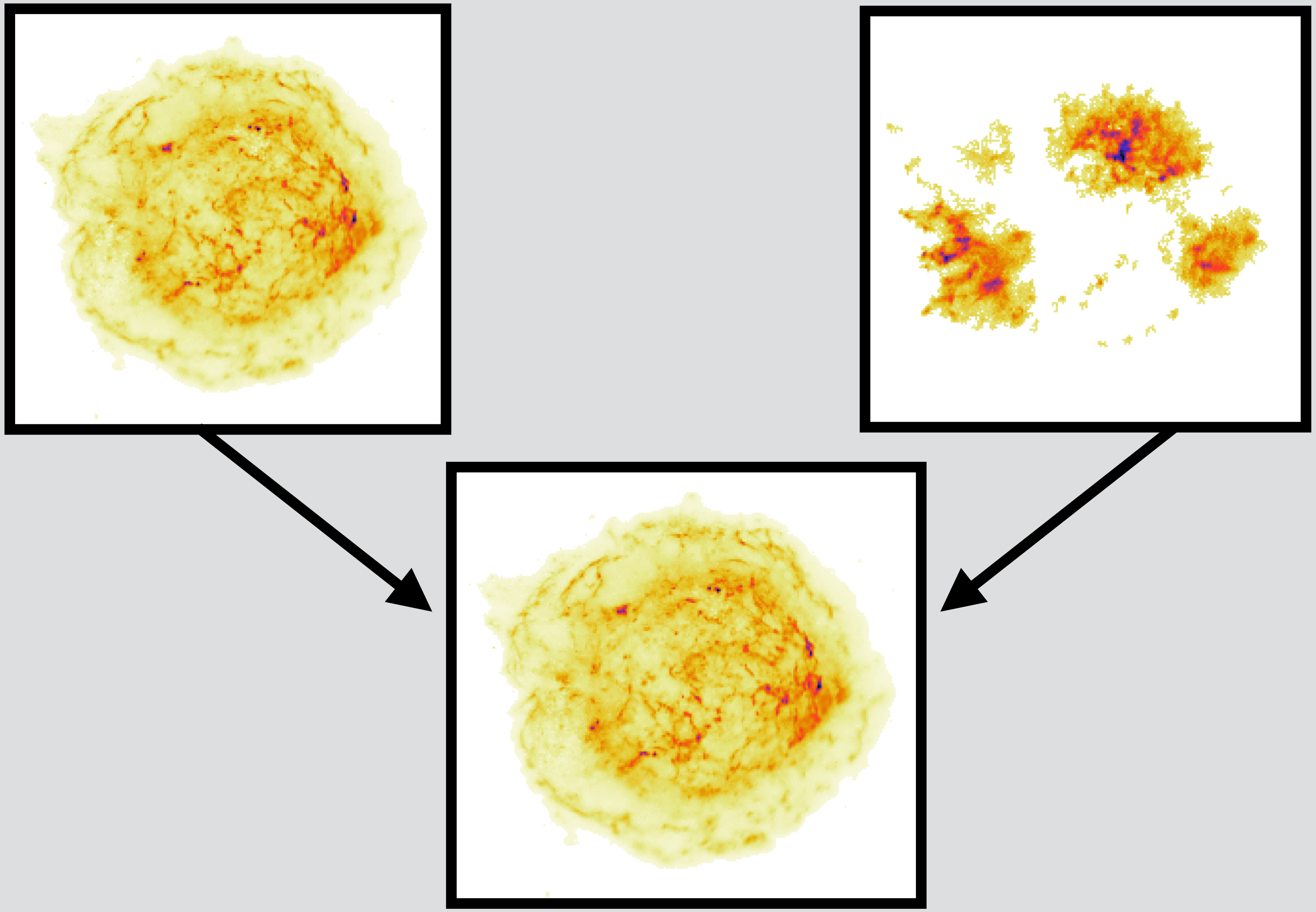
Test on toy models

Our two toy models have two components :



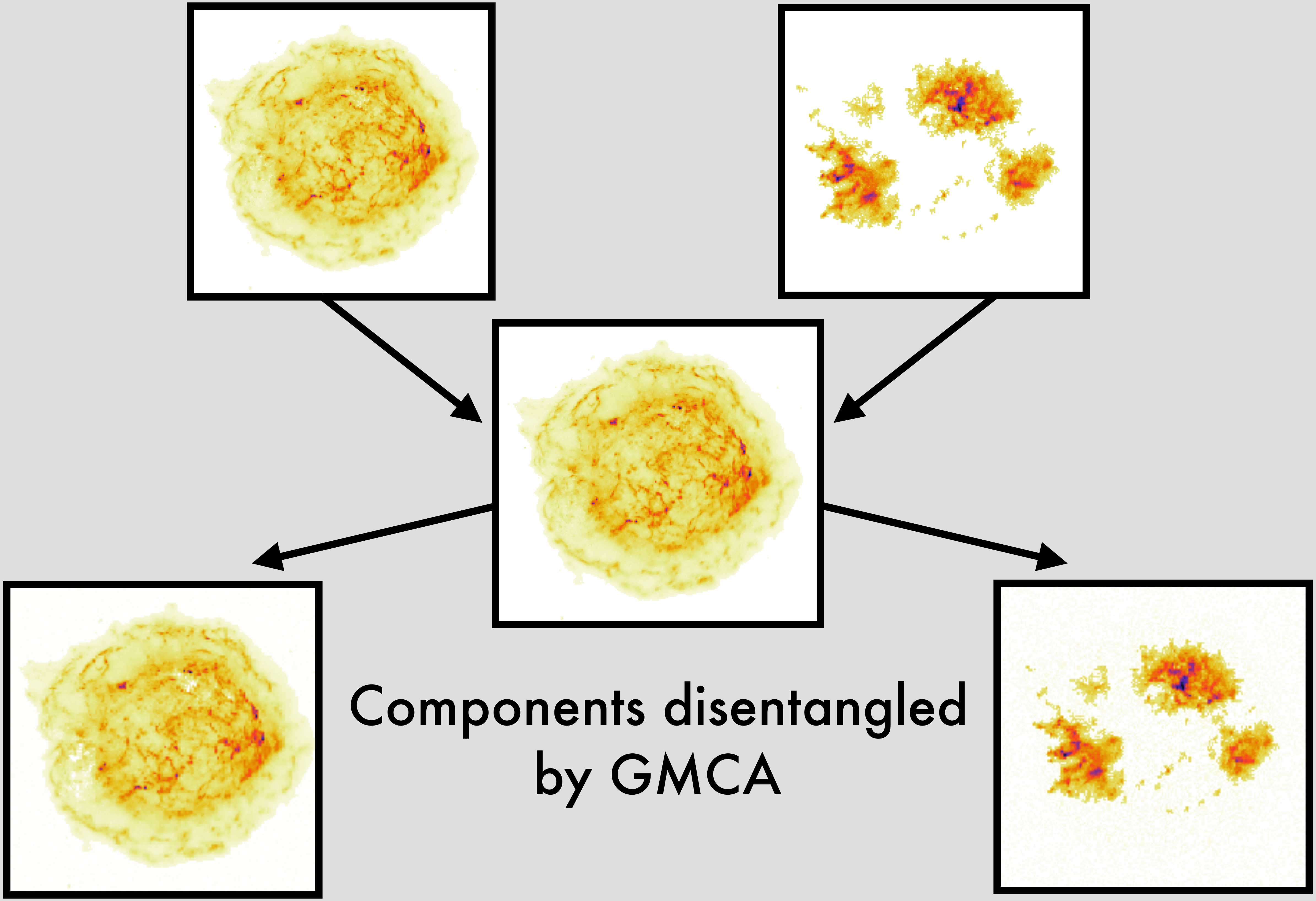
The first component is a synchrotron emission, the second one is either a thermal emission or a line emission. We generate Poisson noise.

Test on toy models



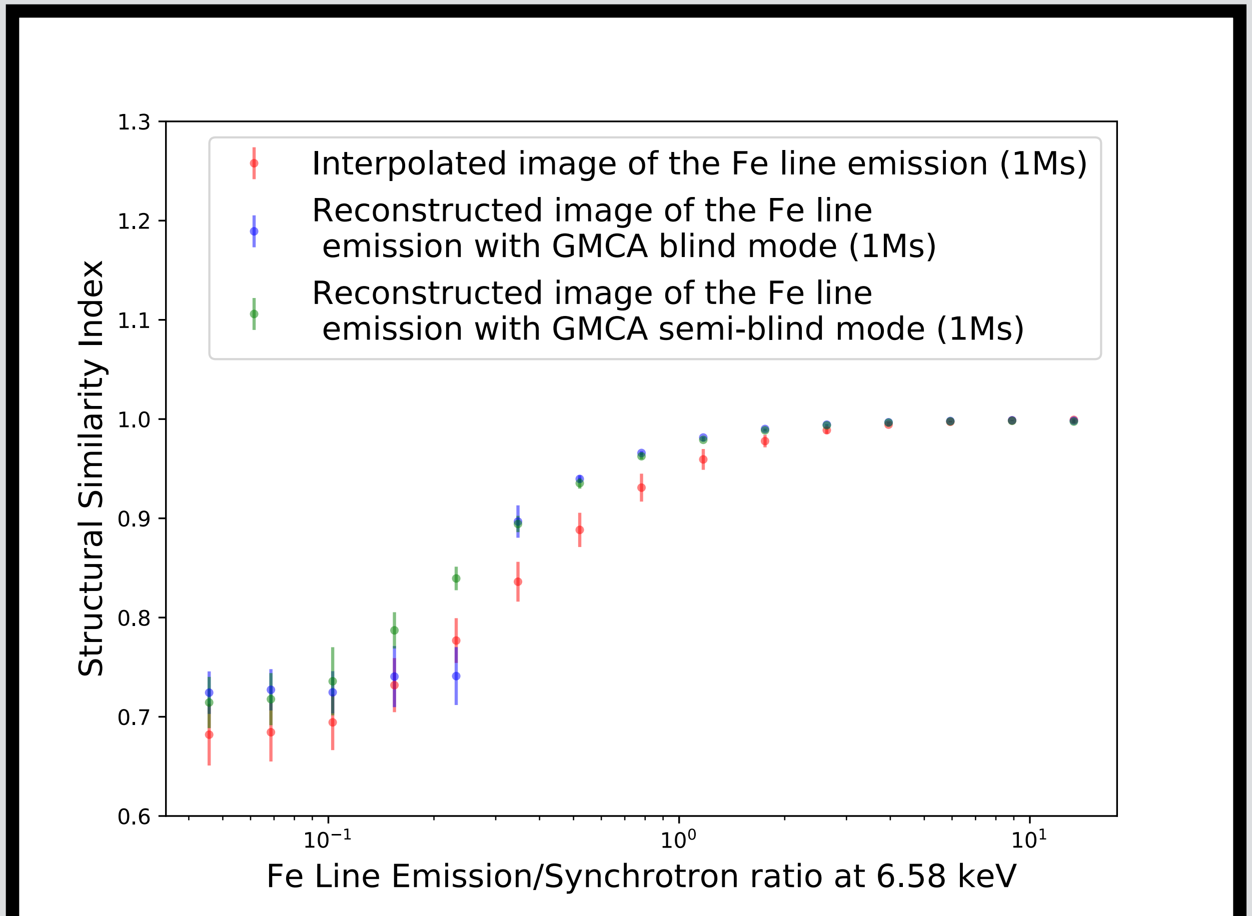
Both components are entangled in our toy model

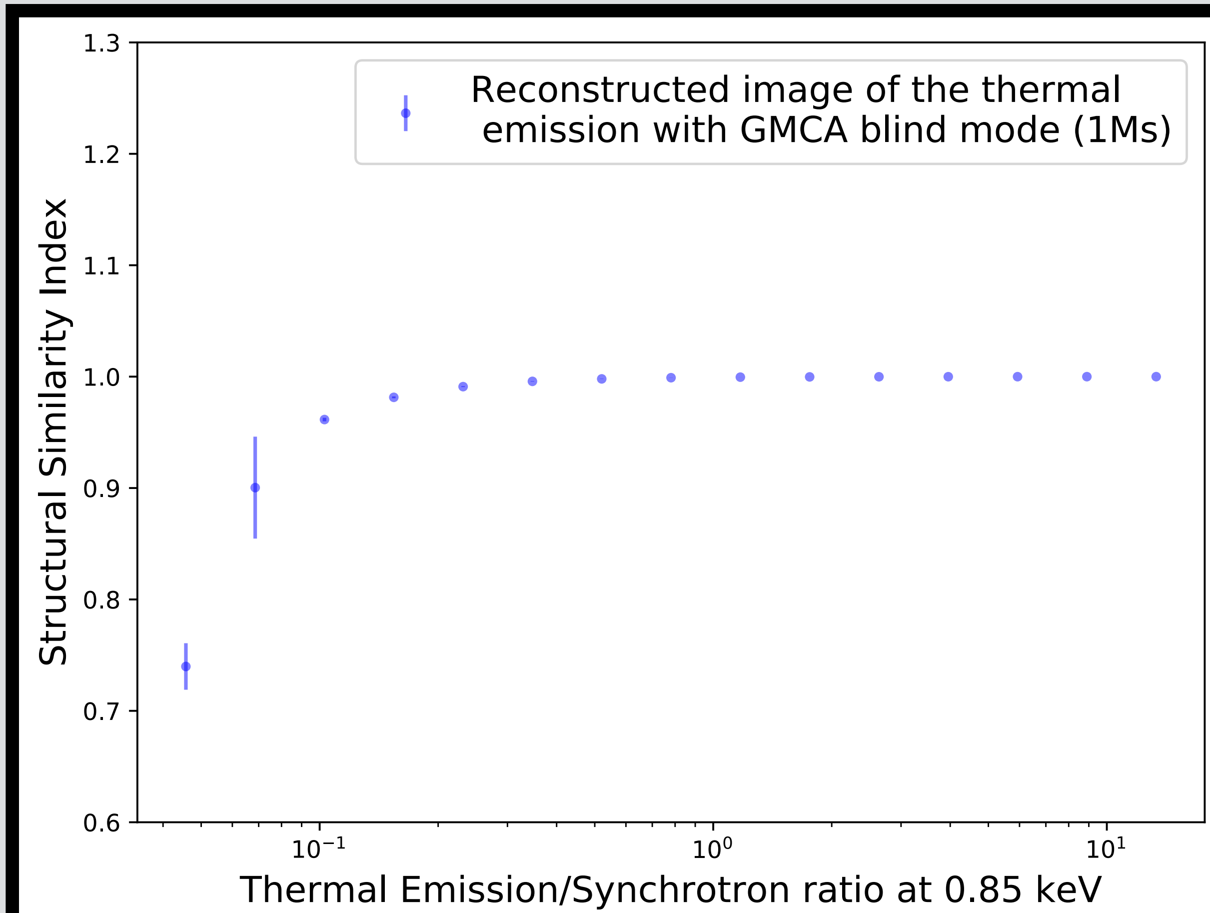
Test on toy models



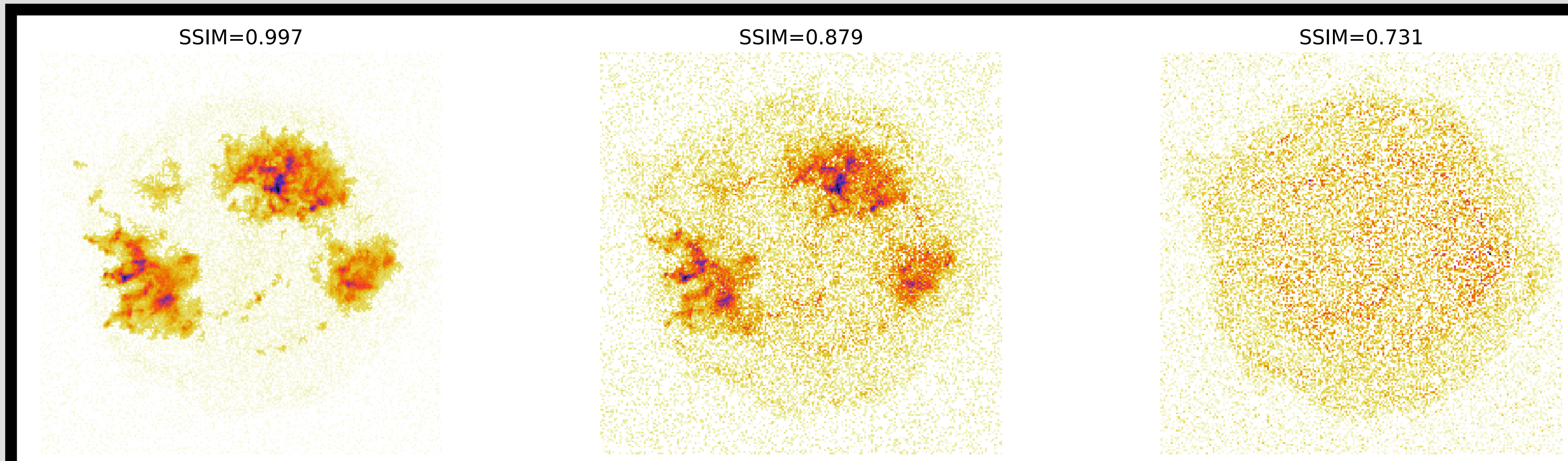
Components disentangled by GMCA

Reconstructed image accuracy



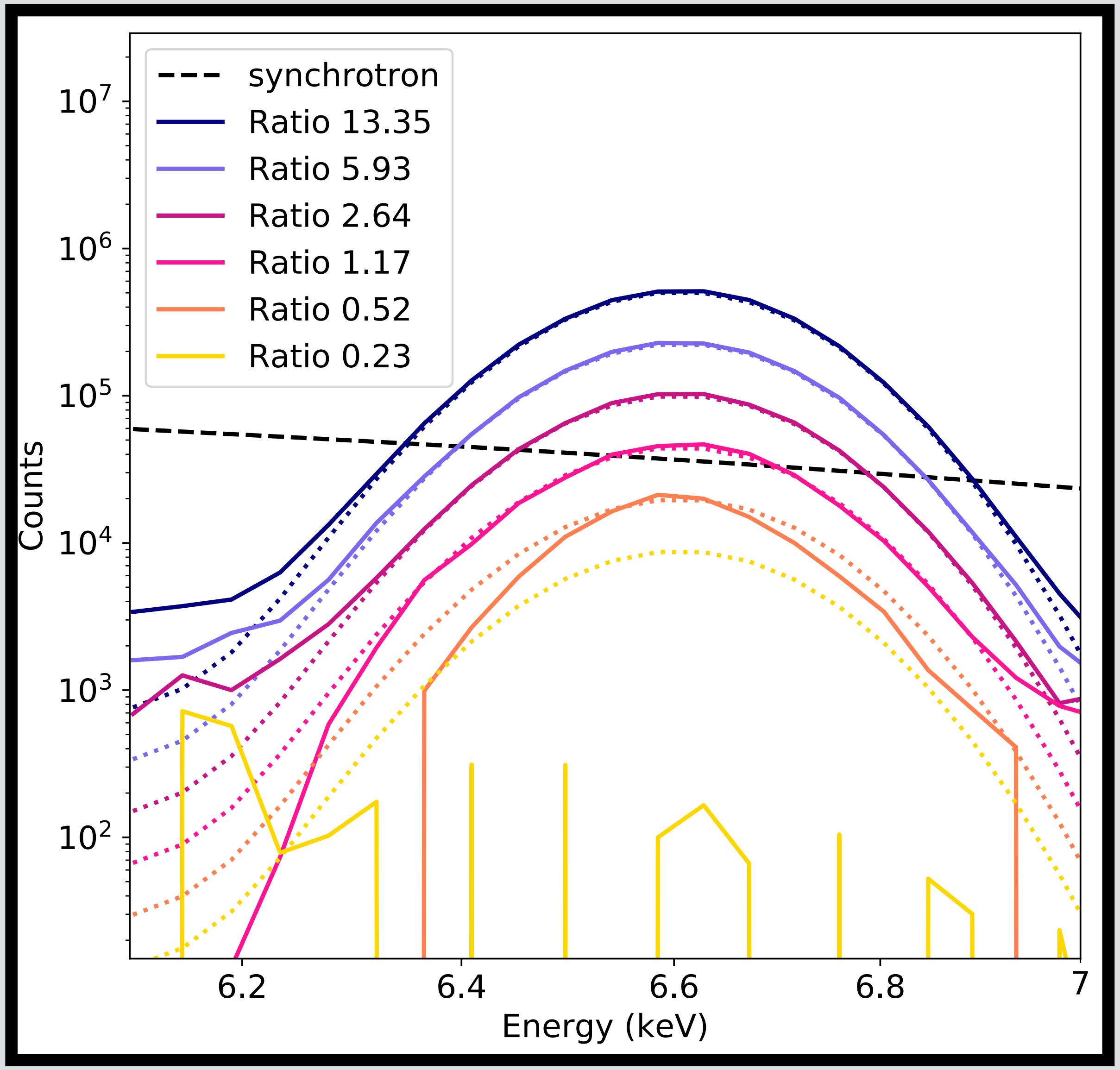


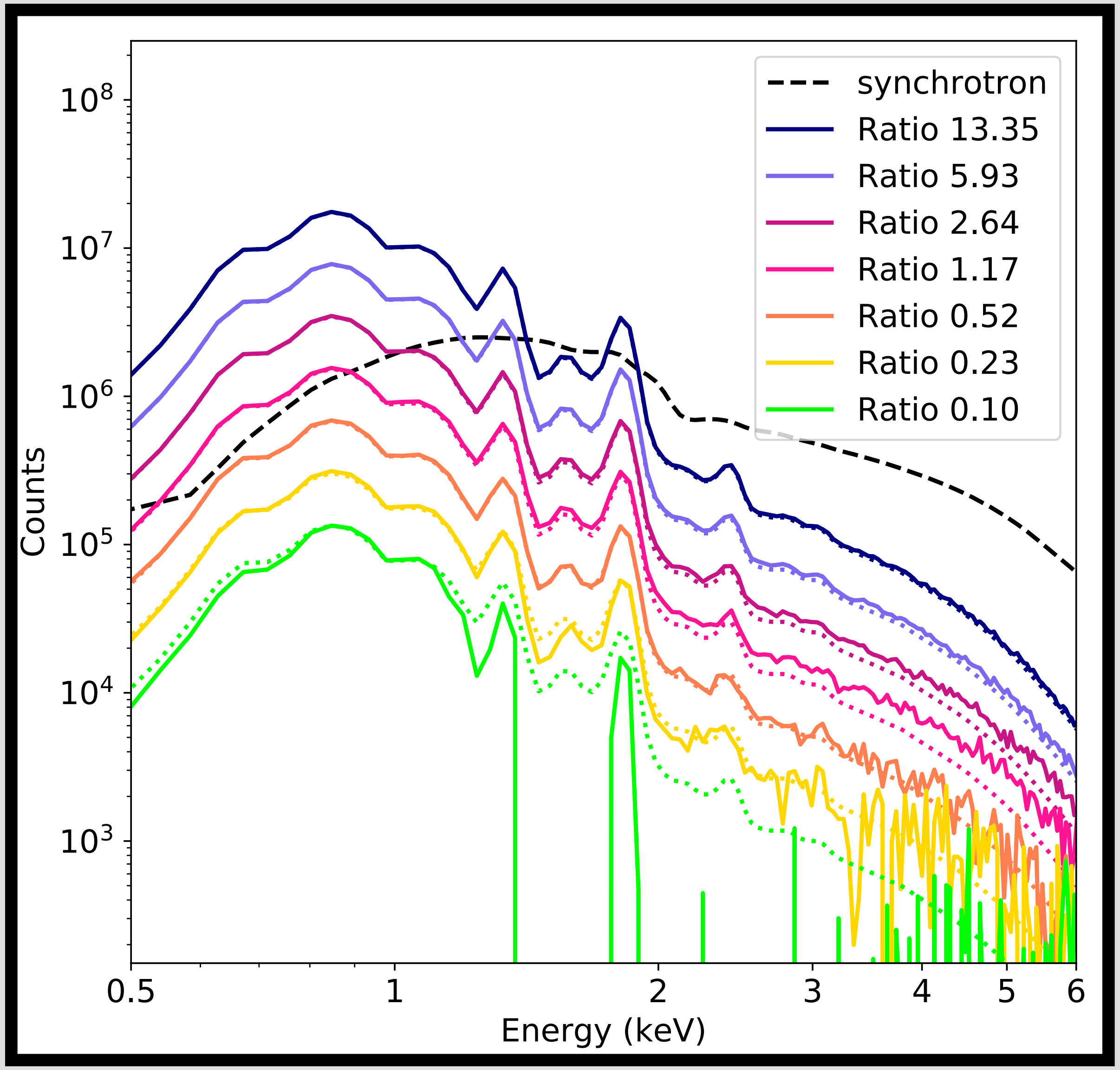
SSIM coefficients of the images of the retrieved second component in both toy models



Examples of SSIM coefficients associated with the corresponding images

Spectral accuracy

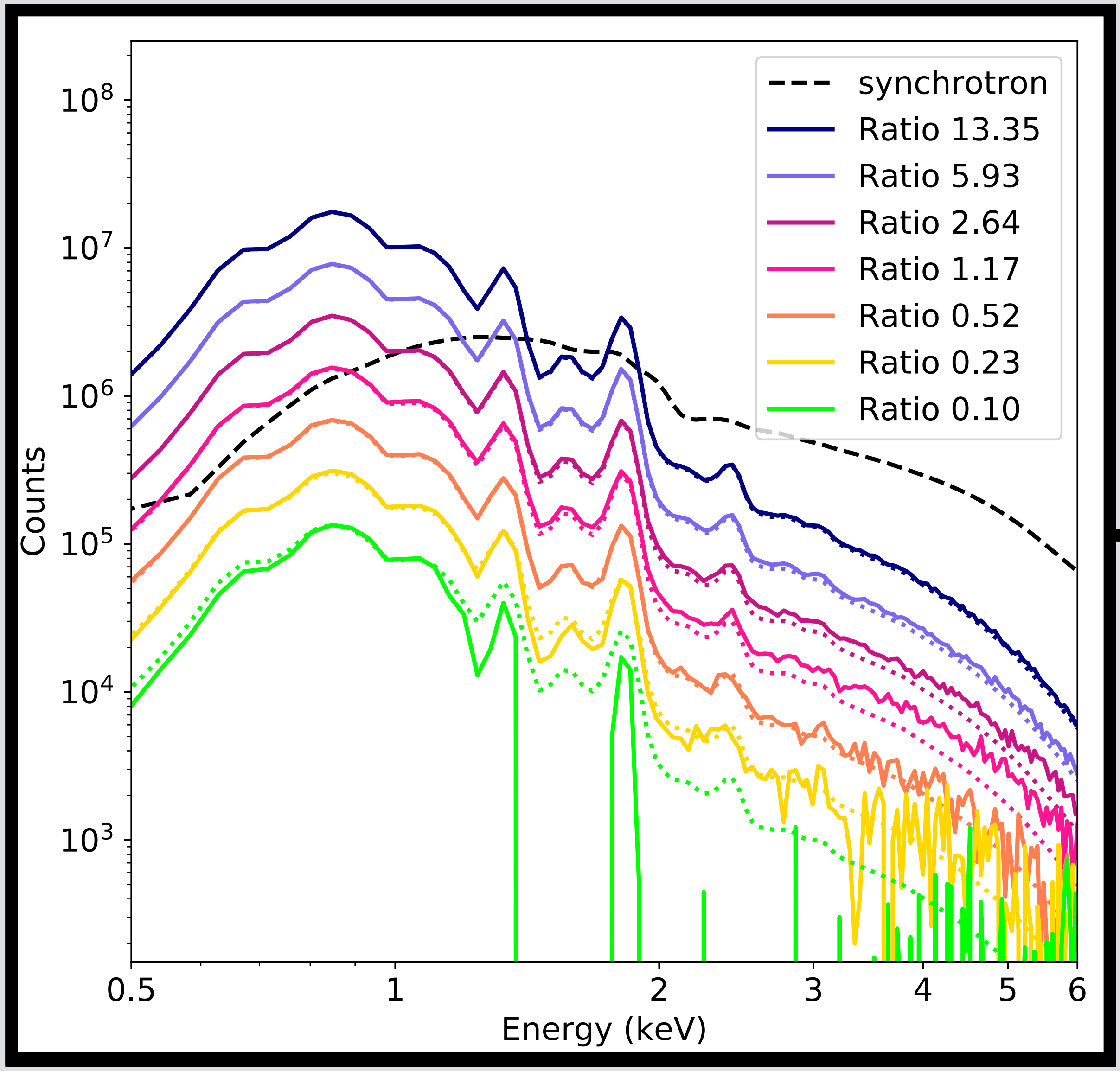


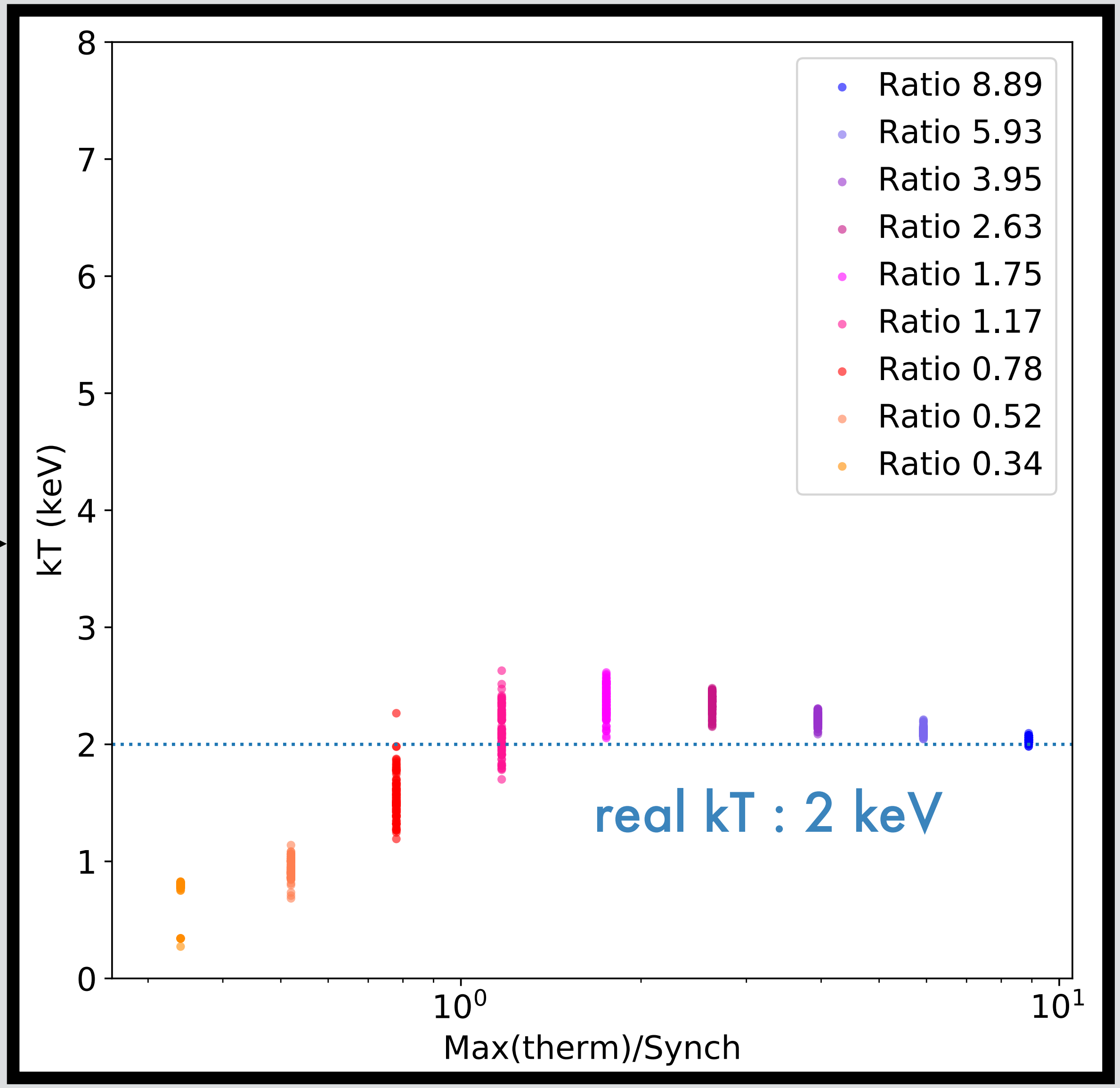


Spectra of second component retrieved by GMCA in both toy models

The dashed lines represent theoretical models. On the right, we can see important deviations in high energy from the model.

Spectral accuracy





Retrieved kT

After a fitting in Xspec.

Application on real data

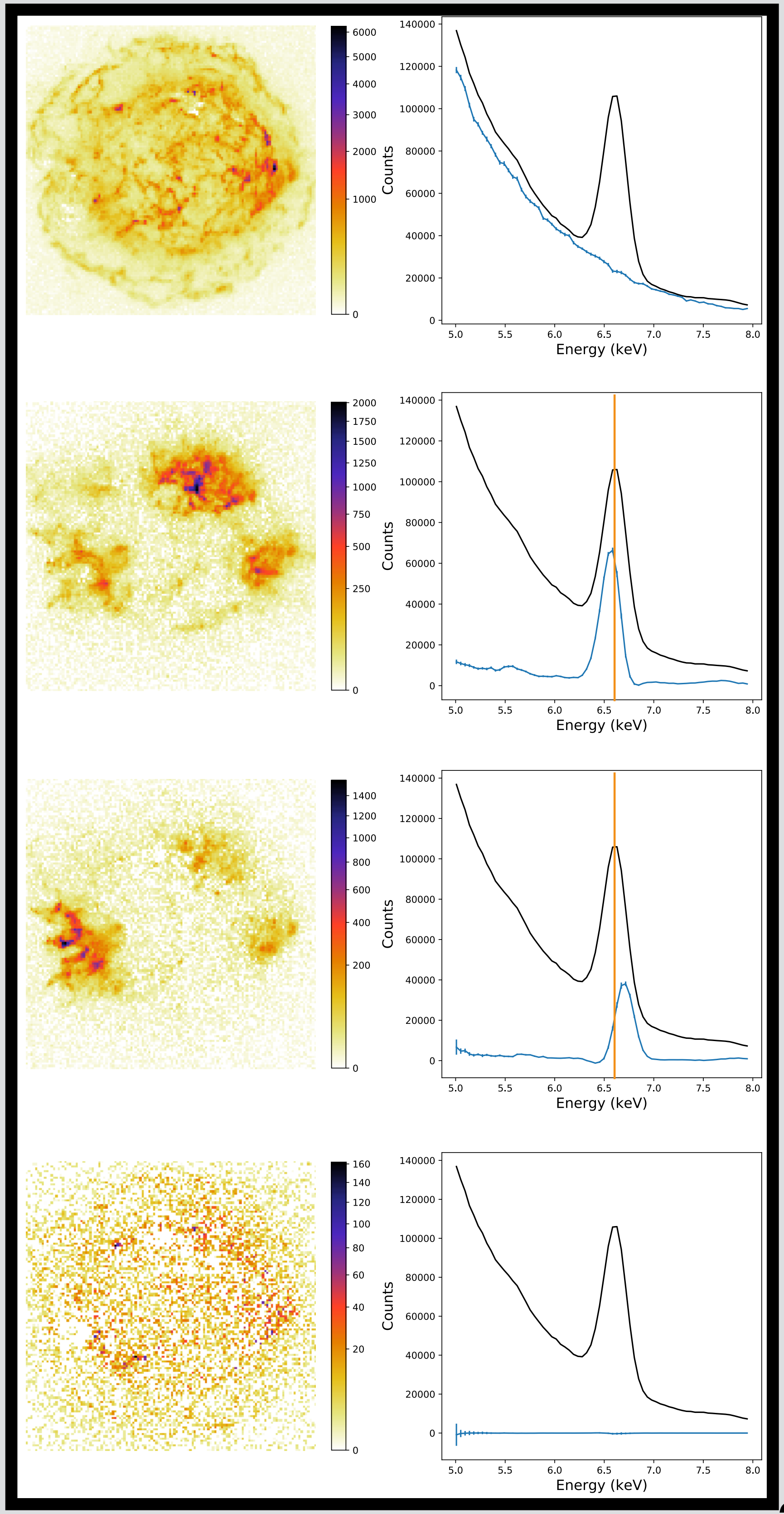
Application between 5 and 8 keV :

Synchrotron

Red-shifted Fe structure

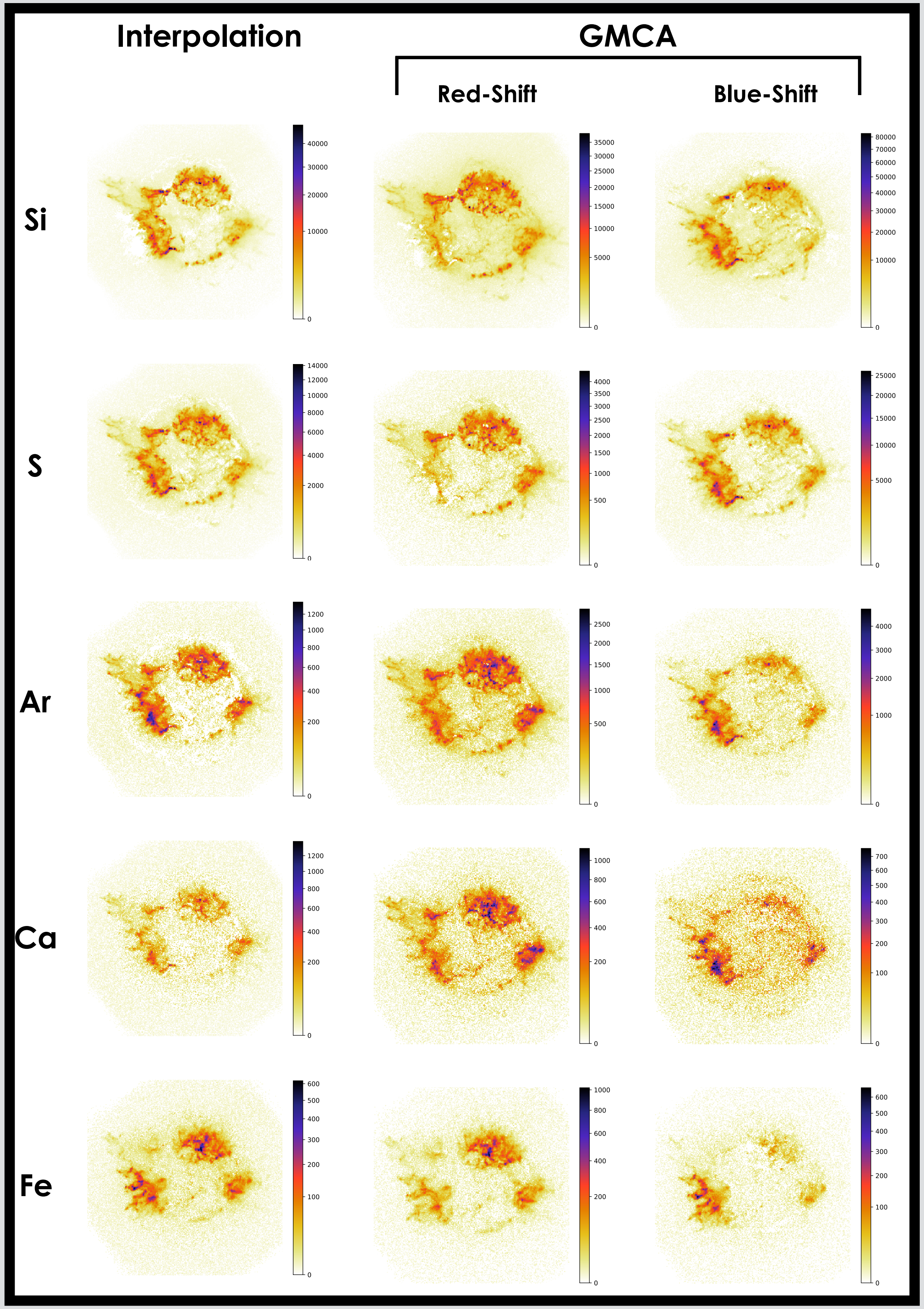
Blue-shifted Fe structure

Noise



Application on real data

<u>Application around each major line emission:</u>



Conclusion

- GMCA retrieves morphologically and spectrally accurate components.
- The performances of the algorithm are very case-specific
- Bootstrap resamplings give accurate error bars
- First applications on real data are very promising, offering a lot of new information to do science !

Astronomy & Astrophysics manuscript no. main ©ESO 2019
Saturday 5th January, 2019

A novel method for component separation of extended sources in X-ray astronomy

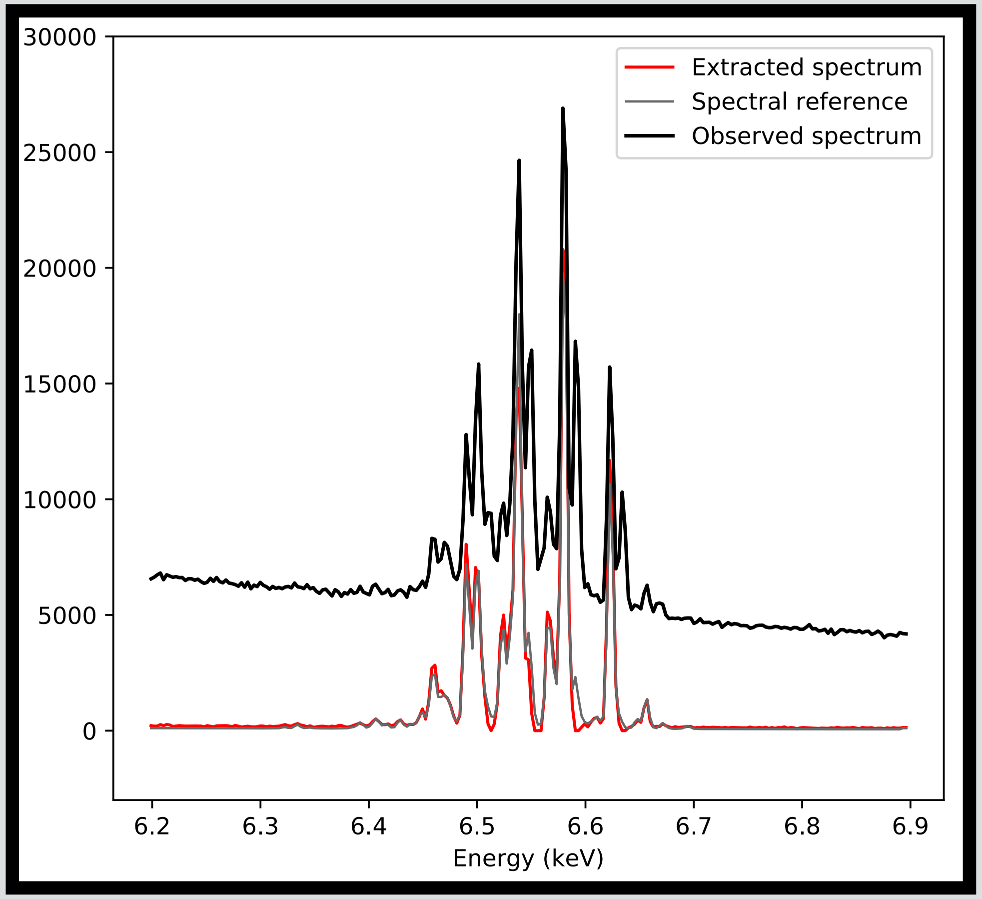
A. Picquenot[1], F. Acero[1], J. Bobin[1], P. Maggi[2], J. Ballet[1], and G.W. Pratt[1]

[1] AIM, CEA, CNRS, Université Paris-Saclay, Université Paris Diderot, Sorbonne Paris Cité, F-91191 Gif-sur-Yvette, France e-mail: adrien.picquenot@cea.fr, fabio.acero@cea.fr
[2] Observatoire Astronomique de Strasbourg, Université de Strasbourg, CNRS, 11 rue de l'Université, F-67000 Strasbourg, France

The methodology paper has been submitted

Perspectives

- The method will be developed to take into account mosaic-like data (for example on RXJ 1713)
- Dictionary of physical spectral shapes, to « help » the algorithm with further information
- HESS / CTA : Feasible, but in need of an energy dependent PSF handling.
- A promising method for Athena :



Toy model of Athena X-IFU data (2eV of resolution, vs. 120 eV for Chandra) of Cassiopeia A (100ks) around the Fe line