COMPONENT SEPARATION FROM POISSON MEASUREMENTS WITH APPLICATIONS IN ASTROPHYSICS

Keywords. Sparse signal modeling, sparse representations, blind source separation, multivalued data, Poisson process.

Context. Blind source separation (BSS) is one of the most powerful methods for analyzing multi-observation data, such as for instance multispectral/hyperspectral images. In this context, one has access to multiple and different snapshots of the same phenomena. Whether it is an image, time series or others, each observation x_i is described as the linear combination of elementary signals or sources to which noise is added :

$$x_i = \sum_j a_{ij} s_j + n_i, \tag{1}$$

where the scalars $\{a_{ij}\}$ describe the contribution of each source $\{s_j\}$ in the data. The goal of blind source separation is to extract both the mixture parameters $\{a_{ij}\}$ and the sources $\{s_j\}$ assuming only the observations $\{x_i\}$ are known, which is known to be a challenging ill-posed inverse problem (see [1]). During the last decade, the concept of sparsity is at the origin of the development of highly efficient source separation methods (see [2,3]). In brief, this approach relies on the sparse modeling of the inner geometrical content of the sources to be estimated in some transformed domain (*i.e.* Fourier, wavelets, curvelets, etc.).

Goal and method. However, in many applications such as optics and astrophysics, the observations are not precisely described by the mixture model of Equation 1, but are rather Poisson processes. A more precise model consists in describing the measurements as multichannel Poisson processes :

$$x_i \sim \mathcal{P}_{\text{oisson}} \left(\sum_j a_{ij} s_j \right) \tag{2}$$

In this context, the main challenge is that the state-of-the-art blind source separation techniques are not adapted to the analysis of such multichannel Poisson measurements, which further hampers their ability to succeed in accurately estimating the mixture parameters and the sources. The goal of this project is to investigate the development of a new sparse blind source separation algorithm for solving blind source separation problems from Poisson measurements. These developments will take their roots in sparse BSS [5] and proximal algorithms [4].

These developments will have a major impact in astrophysics projects such as the Fermi space mission [1], Chandra [2] or XMM [3], where the ability to precisely account for the Poisson distribution of the observations is critical to provide an accurate

1. *http ://fermi.gsfc.nasa.gov/.*
2. *http ://chandra.harvard.edu/*
3. *http ://www.cosmos.esa.int/web/xmm-newton*

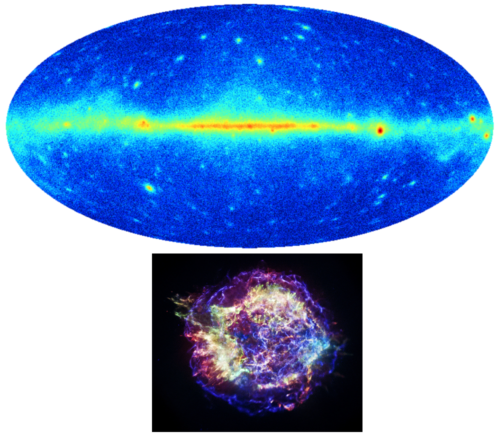

FIGURE 1. Top : one observation channel of the FERMI data (Gamma-ray emission). Bottom : Chandra X-ray telescope - snapshot of the Cassopeia A. The very nature of the Poisson measurements makes the extraction of relevant sources highly challenging.

decomposition of the data.

Candidate. The candidate should be a Master 2 student (or equivalent) and should have a good knowledge in signal/image processing. Knowledge in convex optimization is a plus.
During this internship, the candidate will acquire knowledge in various fields of signal/image processing : i) sparse signal representations (*e.g.* wavelets, curvelets,.) and their application to tackle inverse problems in imaging, ii) blind source separation methods, iii) modern-day optimization methods such as proximal algorithms.

Contact information.

— *Contact :* jbobin@cea.fr or cecile.chenot@cea.fr
— *Lab :* CEA/IRFU in Saclay, `http://www.cosmostat.org`

— *Duration :* at least 4 months
— *PhD :* yes
— **Applications are expected before the 28th of February 2017.**

Bibliography. [1] P. Comon and C. Jutten, **"Handbook of blind source separation"**, Academic Press, 2010.
[2] J.Bobin *et al*, **"Sparsity and Morphological Diversity in Blind Source Separation"**, IEEE Tr. on Image Processing, 2007.
[3] J.Bobin *et al*, **"Sparsity and adaptivity for the blind separation of partially correlated sources "**, IEEE Tr. on Signal Processing, 2015.
[4] N. Parikh and S. Boyd, **"Proximal Algorithms "**, Foundations and Trends in Optimization, 2014.
[5] J.Rapin *et al*, **"NMF with Sparse Regularizations in Transformed Domains "**, SIAM Imaging Science, 2014.