RETRIEVING SOURCES WITH SPATIALLY-VARIANT MIXTURE MODEL IN ASTROPHYSICAL DATASETS

Keywords. Sparse signal modelling, sparse representations, blind source separation, multivalued data, non-stationary mixture model.

Context. Component separation plays a key role in a very large range of scientific applications such as in medical signal and image analysis or astrophysics. In this context, the data are composed of multiple 2D observations $\mathbf{x}_i$, each of which is assumed to be composed of the combination of several elementary components or sources s_j. The current state-of-the-art model is the linear mixture model that assumes a linear relationship between the sources to be retrieved and the observed signal x_i. This is described as follows :

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

where the scalars $\{a_{ij}\}$ describe the contribution of each source $\{s_j\}$ in the data. The goal of component separation is to extract both the mixture parameters $\{a_{ij}\}$ and the sources $\{s_j\}$ assuming only the observations $\{x_i\}$ are known. A simple illustration is given in Fig.1 that features a single observation x_i provided by the Chandra X-ray telescope [1]. This observation can be described as the combination of various astrophysical components such as the synchrotron emission or atomic emission lines. The goal of component separation is to estimate each of these components from the observations. In this context, the mixing matrix $\mathbf{A} = [a_i j]$ contains the spectral signatures of these components and the source matrix $\mathbf{S} = [s_j]$ describes their spatial distributions.

1. *http ://chandra.harvard.edu/*

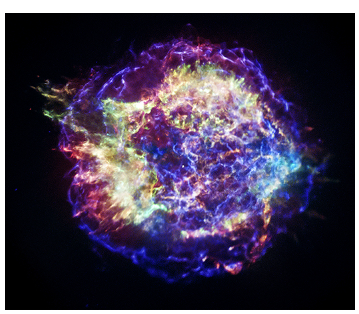

FIGURE 1. **Chandra X-ray telescope - snapshot of the Cassopeia A.** The sources to be retrieved are associated with the various astrophysic components such as specific atomic lines (*e.g* Argon, Sulfur, Iron, etc.).

Goal and method. The mixture model described above is however a crude description of the relationship between the observation and the components to be retrieved. A refined modelling of these data should account for the variation across pixels of the spectral signatures of the sources. Indeed, instead of assuming that the mixing matrix is the same for all the observed pixels, the mixing matrix should be allowed to across pixels k :

$$x_i[k] = \sum_j a_{ij}[k] s_j[k] \tag{2}$$

However component separation is known to be a challenging ill-posed inverse problem (see [1]), which requires using extra information to discriminate between the sources. During the last decade, the concept of sparsity is at the origin of the development of highly efficient source component separation methods methods (see [2,3]).

However, in many applications such as optics and astrophysics, the obsererva-tions are rather Poisson In this context, the main challenge is that the state-of-the-art blind source separation are not adapted to analyze 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 [2], Chandra [3] or XMM [4], where the ability to precisely account for the Poisson distribution of the observations is critical to provide an accurate 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.

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— *Lab :* CEA/IRFU in Saclay
— *Duration :* at least 4 months
— *PhD :* yes
— **Applications are expected before the 28th of february 2017.**

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

Bibliography. [1] P. Comon and C. Jutten, **"Handbook of blind source separation"**, Academic Press, 2010.
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[5] Rapin *et al*, **"NMF with Sparse Regularizations in Transformed Domains "**, SIAM Imaging Science, 2014.