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Sparse Spatio-Temporal Imaging of Radio Transients†

Poster on-line

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Abstract. The next-generation radio telescopes such as LOFAR and SKA will give access to high time-resolution and high instantaneous sensitivity that can be exploited to study slow and fast transients over the whole radio window. The search for radio transients in large datasets also represents a new signal-processing challenge requiring efficient and robust signal reconstruction algorithms. Using sparse representations and the general 'compressed sensing' framework, we developed a 2D–1D algorithm based on the primal-dual splitting method. We have performed our sparse 2D–1D reconstruction on three-dimensional data sets containing either simulated or real radio transients, at various levels of SNR and integration times. This report presents a summary of the current level of performance of our method.

Keywords. Methods: data analysis, techniques: interferometric

1. Introduction

The new giant radio facilities like LOFAR (van Haarlem *et al.* 2013), MeerKAT/SKA and ASKAP/SKA (Dewdney *et al.* 2009) come with high spectral, temporal and angular resolutions and huge instantaneous sensitivity. In order to detect transient radio sources like pulsars, rotating radio transients (RRATs), fast radio bursts, solar-system magnetised objects, etc., one needs to rely on robust transient detection tools working at all temporal scales, from millisecond to weeks or months. Searching for signals from transients in huge datasets generated at high resolution also represents a hard data-processing challenge which classical methods cannot absorb. It is hoped that, with the recent framework of Compressed Sensing (Candès *et al.* 2006, Donoho 2006) and sparse representations, it will be possible to start addressing this problem.

Radio transients can be classified broadly into two classes:

• 'Slow' transients, mostly generated from incoherent synchrotron emissions, showing relatively low variability (minutes to months or a year). They are usually associated with explosive events radio counterparts such as X-ray binaries, Magnetar outbursts, SN, AGN, Tidal Disruption Events, Gamma-Ray Bursts (Fender & Bell 2011). Detections are made mainly in images obtained from multi-spectral observations.

• 'Fast' transients, associated with coherent emission processes, present fast variability ($\leqslant 1$ min). The sources can be pulsars, Rotating Radio Transients (RRATs), (exo)planets, flaring stars, solar bursts and (more recently) Fast Radio Bursts (Lorimer *et al.* 2007, 2013; Thornton *et al.* 2013; Spitler *et al.* 2014; Petroff *et al.* 2015); their detections are usually made with time series or time-frequency spectroscopy (a.k.a. dynamic spectroscopy).

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In this work we focus mainly on transient detection using the imaging mode of a generic radio interferometer. Detection of transients through direct imaging depends mostly on the quality of the data calibration, on the performance and on the rate of imaging using aperture synthesis. We have proposed a novel approach for addressing the deconvolution and the detection of radio interferometric images, accounting for both spatial and temporal dependency of the data.

2. Methodology

2.1. *The motivation for sparse representations*

Classical transient detection methods operating on radio images rely on comparing the result of a source detection algorithm in a series of time integrated images such as TraP (see Swinbank *et al.* 2015). The detectability of a transient will therefore depend on the temporal resolution of an image. However, in a blind search for transients the duration of a transient event is unpredictable. For a steady source, time and frequency integration can help to improve the detection SNR in the image. For a highly variable source, long-time integration will be detrimental for the detection owing to temporal smearing (or 'dilution'). Conversely, if a series of noisy snapshot images is produced to detect a transient, there is no guarantee that the SNR of the image will add towards a robust detection of it.

Interferometric data are samples of the Fourier transform of the sky brightness sampled at spatial frequencies (time and frequency dependent) corresponding to all projected baselines towards a source. From those sets of samples, an image can be formed using a given time (or frequency) integration window. There is scope to search for an appropriate space for representing the data that could grasp the temporal structure of the signal. The Fourier space is appropriate for representing periodic features in a signal (e.g. pulsars), while wavelet-class transforms are more suitable for single pulses. Transforming a signal in its appropriate space is searching for a 'sparse' representation of it. This signal can be represented by only a small set of its relevant coefficients in that space, thus improving detection.

2.2. *Casting the transient imaging problem as an inverse problem*

The interferometry imaging problem constitutes an ill-posed inverse problem that can be written, in a simplified form, as in Eq. 2.1:

$$\mathbf{V} = \mathbf{MFx} + \mathbf{N} \tag{2.1}$$

where $\mathbf{V}$ is the measured visibility vector, $\mathbf{M}$ is the sampling mask which accounts for time-dependent incomplete sampling of the interferometer in Fourier space, $\mathbf{F}$ is the FT operator, $\mathbf{x}$ is the time-dependent sky, and $\mathbf{N}$ is the noise. The sky $\mathbf{x}$ is expressed here in the 'direct' 3D space (2D for space and 1D for time). A sparse representation of $\mathbf{x}$ can be given with a compact set of relevant coefficients α_i. If we call Φ the transform operator from this sparse domain to the direct domain, we can write $\mathbf{x} = \Phi\boldsymbol{\alpha}$. The corresponding 2D–1D sparse representation represented by Φ and Φ^T is vital to the quality of the final reconstruction.

As described in Starck *et al.* (2009), an adequate wavelet function would be $\psi(x, y, t) = \psi^{(xy)}(x, y)\psi^{(t)}(t)$, where space (xy) and time (t) are independent, and $\psi^{(xy)}$ is chosen to be the spatial isotropic undecimated wavelet function (or Starlets, Starck *et al.* 2011), and $\psi^{(t)}$ is a decimated wavelet function (either 9/7 or Haar wavelets).

Having defined the 2D–1D dictionary Φ, we can derive the minimisation problem in the analysis framework from Eq. 2.1, and after some mathematical developments (details of which are given in the poster), we obtain

$$\min_{\mathbf{x}} ||\mathbf{V} - \mathbf{MFx}||_2^2 + k_1||\mathbf{W} \odot \boldsymbol{\lambda} \odot \boldsymbol{\Phi}^t\mathbf{x}||_1 + k_2 i_{\mathbb{C}^+}(\mathbf{x}), \tag{2.2}$$

The objective function can be decomposed into three terms: (1) the data fidelity term (using the l_2-norm from 2.1), (2) the sparsity constraint given by the $||\boldsymbol{\Phi}^t \cdot ||_1$, where the l_1-norm is the sum of the absolute values of the coefficients to reinforce the sparsity of the solution and ensure the convexity of the problem, and (3) the positivity constraint. $\mathbf{W}$ and $\boldsymbol{\lambda}$ are respectively weights and scale-dependent thresholds in the Lagrangian form of the Reweighted-l_1 formulation (Candes *et al.* 2007). $i_{\mathbb{C}^+}$ denotes the indicator function in the positive set $\mathbb{C}^+$, and k_1 and k_2 are the two relaxation parameters to define trade-offs between sparsity, positivity and data fidelity. In our study, using the Condat-Vũ splitting method (CVSM; Condat *et al.* 2013; Vũ *et al.* 2013, and also used in our previous work dedicated to 2D-only sparse reconstruction in Garsden *et al.* 2015), a variation of primal–dual algorithms was used to solve the inverse problem with the scheme of Eq. 2.2.

3. Preliminary Results

3.1. *Data preparation*

In order to test our method, we carried two numerical experiments: (1) from a simulated dataset containing a steady source and a transient source sampled by a small realistic interferometer, and (2) a real EVLA interferometric dataset containing a single pulsar pulse from B0355+54 (not discussed here; see the online poster (URL on p. 303) for details).

In the first experiment, we simulated a 2-hour observation with one control source in the centre of the field, and one transient offset source. We then prepared raw datasets by injecting various levels of noise (σ) and rebinning the data artificially in time (τ) to simulate a continuous span of short- and long-time integrations. We could explore the efficiency of reconstruction in a 2D parameter space defined by the time integration τ and the injected noise σ, and we chose the injected noise level range from no noise to twice the detectability limit ($\sigma \sim S$, where S is the peak flux of the source transient source at its maximum). The time integration was defined as the number of temporal frames that covered the 2-hour observation with a minimum of two frames (two frames of 1-hour integration) up to 256 frames (each frame is ∼30s). The transient was simulated to follow a Gaussian light-curve of width 2.5 min, centred in the middle of the observation.

3.2. *Reconstruction of the simulated data*

The 9^{th} image in the online poster (URL on p. 303) presents the reconstructed SNR of the peak flux of the transient source in the (σ, τ) parameter space for three reconstruction algorithms: (1) a direct inversion of the gridded data (the ‘dirty image’), (2) after we applied a simple CLEAN algorithm (Högbom 1974) to each temporal frame, and (3) the reconstruction with the 2D–1D method. The dirty image SNR map shows how a single transient pulse can be detected depending on the level of injected noise (high noise is at the top of each plot, no noise at the bottom) and the effect of time binning (for an identical observation of 2h, small values of time frames correspond to long time-integrated images; large values correspond to short time-integrated/snapshot images). In a low noise regime, the transient becomes undetectable owing to a ‘dilution’ effect when the number of time frames is below 50.

In the CLEANed image cubes the transient can be detected with high SNR even with long-time integration. However, the CLEAN algorithm produces a larger fraction of detections compared to the dirty cubes when higher noise in involved.

For our 2D–1D reconstruction (‘CS’ in the poster), the area of robust detection (e.g. with high SNR) was dramatically improved compared to a regime with only small noise. In the high-noise regime the SNR is a function of the time integration between 0 and 50 time frames. In short time-integration images (large number of time frames), the SNR no longer improves above a noise level of ∼1.3.

3.3. *Conclusions*

We produced a similar map to compare the reconstruction fidelity of the transient profile. To inspect other results in more detail, please see Jiang *et al.* 2015, and the online version of the poster related to this work. From these early results, we have demonstrated that the detection capabilities of our method allow for good reconstruction SNR and improved reconstruction fidelity of the transient pulse. A full analysis of the results, along with the reconstruction code, will be made available in a feature article.

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