Improving SNIa detection using Morphological Component Analysis

Anais Möller
CEA Saclay/Irfu/SPP and Université Paris Diderot 7

Detection of supernovae (SNe) and, more generally, of transient events in large surveys can provide numerous fake detections. In the case of a deferred processing of survey images, this leads to reconstruct complete light curves for all detections which requires sizable processing time and resources. Optimizing the detection of transient events is thus an important issue for both present and future surveys. We present here the optimization done in the SuperNova Legacy Survey for the 5-year data differed photometric analysis. In this analysis, detections are derived from stacks of subtracted images with one stack per lunation. The 3-year analysis provided 300,000 detections dominated by signals of bright objects which were not perfectly subtracted. We developed a subtracted image stack treatment to improve detection of SN-like events using morphological component analysis. This technique exploits the morphology of objects to be detected to extract the signal of interest. At the level of our subtraction stacks, SN-like events are rather circular objects while most spurious detections exhibit different shapes. A two-step procedure was necessary to have a proper evaluation of the noise in the subtracted image stacks and thus a reliable signal extraction. When tested on SNLS 3-year data this procedure yielded a reduction of one fourth of the detections with a loss of less than 6% of faint SN-like events.

1 SNLS Photometric Pipeline

SNLS is part of the Deep Synoptic Survey conducted on the Canada-France-Hawaii Telescope (CFHT). It was designed for detecting hundreds of SNe Ia in a redshift range between 0.2 and 1. Using the MegaCam imager [2], an array of 36 CCD with 340 million of pixels, four one square degree fields were targeted throughout 5 or 7 consecutive lunations using four different broadband filters g_M, r_M, i_M and z_M in the wavelength range from 400 to 1000 nm.

The deferred photometric pipeline of SNLS is independent of the real time standard analysis and classifies SNe using only photometric measurements [3]. The feasability of detecting SNIa with this deferred analysis was proven for the 3-year SNLS data [1].

1.1 Detection of transient events

At CFHT images are preprocessed to perform flat-fielding and to remove defects. Images are then matched to sky coordinates applying an astrometric solution. Reference images are constructed taking a set for each field of best quality images which are coadded. Each image of the survey has the reference image subtracted.

Distant SNe in SNLS are detected in the i_M filter since their maximum flux is at this filter wavelenght. Stacks are constructed coadding all subtracted images in a lunation to increase the signal-over-noise ratio. Detection is done by SExtractor using a signal-over-noise ratio.

Detection for the SNLS-3 yielded around 300,000 candidates dominated by spurious objects due to bad subtraction [1]. An optimization is relevant for the detection of SNe in a larger image sample such as the 5-year SNLS photometric analysis.

2 Optimization on the detection of SNe

Spurious detections have particular shapes and sizes which differ from those of a SN in a subtracted image stack, which can be exploited using morphological component analysis [4].

2.1 Morphological component analysis (MCA)

The hypothesis of MCA is that an image can be decomposed in different dictionaries made from signal atoms [4 5]. An atom is an elementary template which represents a signal, e.g. a sinusoid or a wavelet. A family of atoms at different scales is called a dictionary. An image can be decomposed in a set of given dictionaries. At each scale a threshold can be applied on the decomposition coefficients. The reconstruction of the image is done superimposing selected atoms for a given shape and scale.

2.2 First treatment

Subtracted images contain SNe which are circular-like shaped signals. Spurious detections come mostly from residuals of bright stars, elongated shapes, and other types of residuals as for example imperfect fringe subtraction.

The algorithm by Starck et al. [4] was adapted for the treatment of our subtracted image stacks. Dictionaries chosen for the decomposition were: wavelets(modified starlet and bi-orthogonal wavelet), curvelets and ridgelets. Reconstruction only took into account wavelets at chosen scales and a background of noise residuals. This algorithm supports masks but assumes a stationary and gaussian noise which is not the case in our stacks.

2.3 Second treatment

An utility was developed that handles both non-stationary noise and exploits further morphological decomposition [4]. The utility decomposes the signal in the bi-orthogonal wavelet dictionary and constructs a non stationary noise map using block sizes of 50 pixels. All signals present in the output are considered as transient event candidates.

3 Results

The optimization method was tested on a sample of the 3-year SNLS data within the deferred photometric pipeline. A reduction on the number of detections of almost a factor four is accomplished. The original method yielded 90.971 detections and after the two step treatment only 23.810 remain. Loss of SN-like candidates is less than 6% mostly very faint events not suitable for future cosmological analysis.

The implementation of such optimization for the 5-year analysis gave a similar reduction factor. The original deferred detection resulted in 507.133 detections, while 142.484 detections remained after our optimization .

References

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