A COMBINED MULTIRESOLUTION APPROACH FOR FAINT SOURCE EXTRACTION FROM INFRARED ASTRONOMICAL RAW IMAGES SEQUENCE

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ABSTRACT

Faint sources detection is one of the major issues during the reconstruction of an astronomical science image from a raw data sequence. This problem is a consequence of the detection limit of the infrared instruments as well as the number of cosmic ray impacts (glitches) that leads to the false detection. Astronomical images contain many objects with isotropic structures (e.g. point sources) but also plenty of anisotropic information (e.g. filamentary structures). The wavelet transform is usually applied to separate all these signal constituents in each pixel, then a map is built to represent the information of the associated noise before applying a source detection algorithm. Wavelets are well adapted to point singularities (discontinuities), however, they have a problem with orientation selectivity. Therefore, they do not represent anisotropic structures (e.g. smooth curves) effectively. This paper presents a combined approach contourlet-wavelet for faint source extraction from infrared raw images sequences. While the contourlet representation provides oriented support for efficient approximation of anisotropic structures, isotropic geometry is effectively captured by separable wavelets. This novel approach has been tested on real and simulated infrared images, stemming from the infrared space observatory database.

1. INTRODUCTION

Most of the image processing techniques [12] relies on the presence of geometrical information for efficient object recognition. Astronomy is one of many applications that exploit those techniques for efficient representation of astronomical objects [18]. One of the most critical issues is the detection efficiency of the faint celestial sources from the image background (In astronomy applications, the notion 'background' points out to all what is not relevant for astronomers). This problem raises from the detection limit of the acquisition systems, and thus, the capability to distinguish the faint sources with low contrast from the unwanted background, which is generally a problem in several image processing applications. This paper focuses on the **I**nfra**R**ed (IR) astronomy applications and it will be shown that the proposed analysis can be easily extended to other applications whenever the signal model is known.

1.1. Thermal IR-imaging

Thermal IR-imaging (above 5μm) is a measure of heat. To capture this energy, a complex instrumentation is usually used such that the detectors are cooled down to few kelvins, to not spoil the target signal [11]. Therefore, IR detectors measure a composite signal: source + background. Furthermore, image acquisition is susceptible to cosmic particles (glitches) that might on one side disturb the signal accuracy, changing the electronic characteristics (e.g. responsivity), and on the other side, it might increase the background signal amplitude that may decrease the source extraction efficiency [3, 5].

The science infrared image of NGC 1808 is depicted in Figure 1 is a result of 19 minutes observation of an infrared camera from ISO [5], at 6.7μm with a detector array of 32 X 32 pixels with 16-bit resolution. The quantum of measurement consists, therefore, of a pair of RESET and **E**nd-**O**f-**I**ntegration (EOI) frames. Figure 2 depicts a sequence of 30 selected raw images of this science image (NGC 1808). The white vertical line represents the column 24 with dead pixels, detectors that were lost during the mission. Some images show white dots and curves, which represent the glitches, that influence the EOI raw images calibration.

1.2. Faint Sources

One of the challenging tasks in a reconstruction scheme is the extraction of faint sources from such raw image sequences. Indeed, faint sources usually consist of signal amplitude that is equivalent to the instrument detection limit,

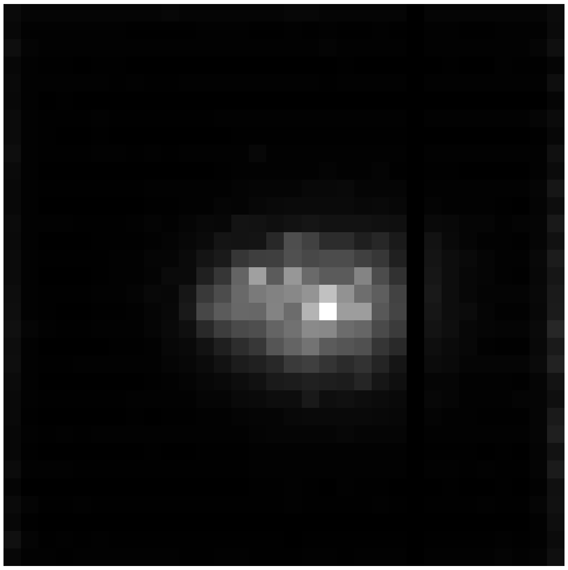

Fig. 1. Starburst galaxy NGC 1808 taken by ISOCAM at 6.7μm

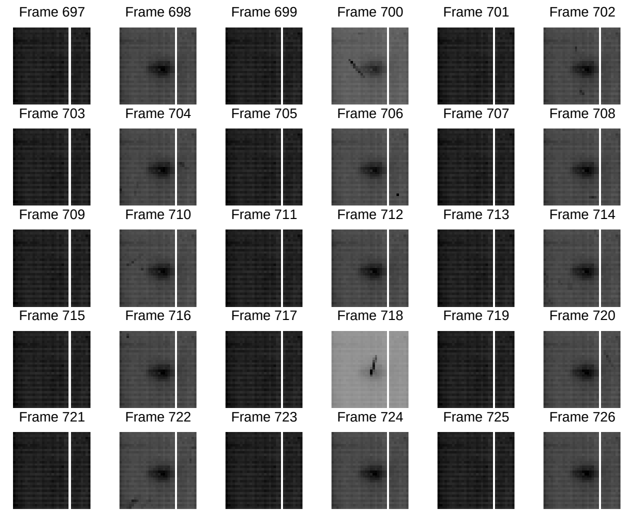

Fig. 2. Selected ISOCAM raw images sequence (30 images) during NGC 1808 observation at 6.7μm (For display reasons, the raw images resolution has been decreased in this figure)

but also the glitch events may cause detector responsivity increases, and therefore, decrease the detection efficiency.

It is a fact that most real life signals are non-stationary. They often contain transient components, sometimes very significant physically, and mostly cover a wide range of frequencies. In addition, there is frequently a direct correlation between the characteristic frequency of a given segment of the signal and the time duration of that segment. Low frequency pieces tend to last a long interval, whereas high frequencies occur in general for a short moment only. Clearly standard Fourier analysis is inadequate for treating such signals, since it loses all information about the time localization of a given frequency component. In addition to that, it is not sparse. Therefore, image analysis turns over to multiresolution wavelet representation.

1.3. Analysis by Multiresolution Wavelet Representations

The A-trous **W**a**V**elet **T**ransform (WVT) [13] is an important tool for faint source detection as used by Starck in [15]. However, it was shown in [6, 7] that separable wavelets can capture only limited directional information, and therefore, cannot represent smooth contours effectively, which are the basis elements in anisotropic features. In [17], the curvelet transform has been used for representation of astronomical image with anisotropic aspects. However, IR astronomical images may contain both isotropic and anisotropic structures (stars and/or galaxies with filamentary structures). Therefore, a combination of methods that preserve both features is required for an improved reconstruction efficiency. Do and Vetterli [7] proposed the **C**on**T**ourlet **T**ransform (CTT), a multiresolution method using directional filter banks. Using sufficient number of directions, this method presents an optimal approximation of geometrical objects with anisotropic structures. To achieve a nearly critical sampling, CTT coefficients are obtained after filtering and decimation of the residual image.

A novel non-decimated version of CTT is presented in this paper, the **U**ndecimated CTT (UCTT). The UCTT is further combined with the A-trous WVT for faint source extraction from IR raw image sequences. The UCTT is applied to smooth resolution images to capture directional geometry, while the A-trous WVT is used for coarse resolution images for the isotropic structures.

This paper can be subdivided into three main parts. In Section 2, the astronomical signal characteristics from infrared detectors and its mathematical formulation are given. In Section 3, the limitation of state-of-the-art separable WVT is illustrated on a smooth contour. It raises from the limited directional information from WVT. Our contribution is presented in Section 4, which consists of a combination of UCTT and A-trous WVT for faint source extraction from IR astronomical images sequence.

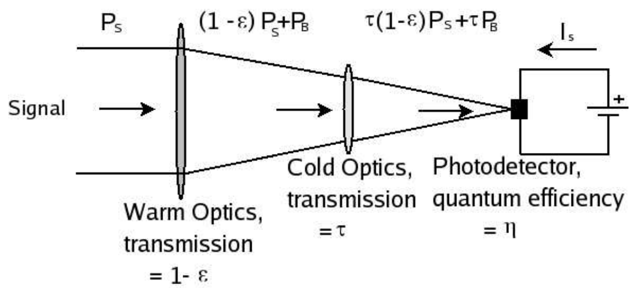

Fig. 3. Light detection with photodetectors

2. PRELIMINARY NOTIONS AND PROBLEM STATEMENTS

This Section presents preliminary notions about the infrared signal formation [3]. Afterwards, the problem of the detection limit for faint sources is exposed.

2.1. Infrared Image Formation with the Photodetectors

Astronomical images are formed by means of a combination of several single photodetectors, called 'detector arrays'. The simplest light detection method possible with photodetectors is incoherent (direct detection), in which the signal involves the photocurrent itself (directly proportional to the power of incident light).

The basic incoherent detection setup is shown schematically in Figure 3. Besides the detector, it is assumed to include some optical elements that can add significant amounts of light to the beam, in addition to that provided by the signal power from a celestial source. The simplest example for the addition of such background light is thermal (blackbody) emission from the optical elements themselves, which is commonly the dominant background source at IR wavelengths and longer (≥ 2 μm) for room-temperature optics. If the transmission of these optics is represented by 1-ϵ, then the signal is reduced by that factor, that is, an incident power P_S is reduced to (1- ϵ)P_S, and ϵ, the effective emissivity of the optics, gives rise to thermal radiation in the amount [3]

$$P_B = \epsilon B_\nu(T)\Delta\nu A\Omega = \epsilon\frac{2h\nu^3}{c^2}\frac{1}{e^{h\nu/kT}-1}\Delta\nu A\Omega, \quad (1)$$

where T is the temperature of these optics, $\Delta\nu$ is the bandwidth of light which we are concerned with (assumed $<<\nu$), and $A\Omega$ is the area-solid angle product of the beam (assumed $<< 4\pi A$). We will refer to any such optical elements as warm. At visible and shorter wavelengths, blackbody emission from optics at normal room temperature is

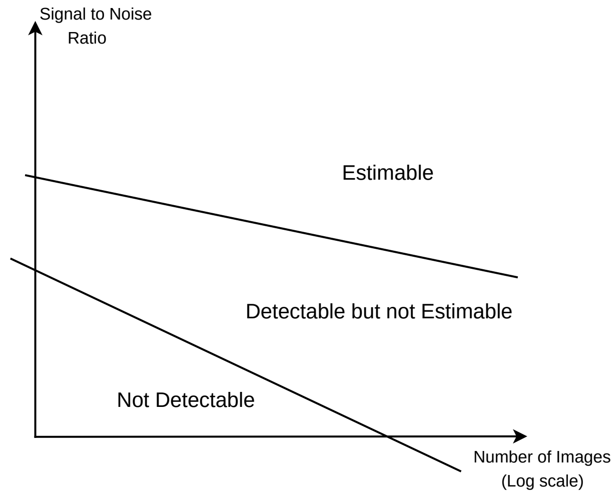

Fig. 4. Illustration of faint source detection and estimation constraints

negligibly small, so such optics can be considered cold in this wavelength range.
Using IR and longer wavelengths as our example, the power incident through the warm and cold optics on the detector is

$$P = \tau(1-\epsilon)P_S + \tau P_B + P_N, \quad (2)$$

(see Figure 3), where P_B is given by Equation 1, and P_N is the noise power. The noise in IR astronomy has several origins: the detectors noise, the amplifier noise..etc [15, 3]. Furthermore, astronomical data suffer from cosmic ray impacts (glitches) as well as from the transient behavior of the detectors, which may cause potential change in the detection limit of the instrument.

We are trying to measure P_S, which is the power from the celestial source, within the wavelength band defined by the filters and within the solid angle Ω.

2.2. The Critical Issues

One of the important criteria in an efficient reconstruction scheme, is the capability of the detection of all source targets within the astronomical images sequences. In other words, the reconstruction process should be able to reerect the source power P_S from the composite power P given in Equation 2. Indeed, this is a critical issue while dealing with faint sources over a high-brightness background and in the presence of noise. Faint sources are celestial objects that emit weak amplitude light, which is usually closer to the background and close to the instrument detection limit.

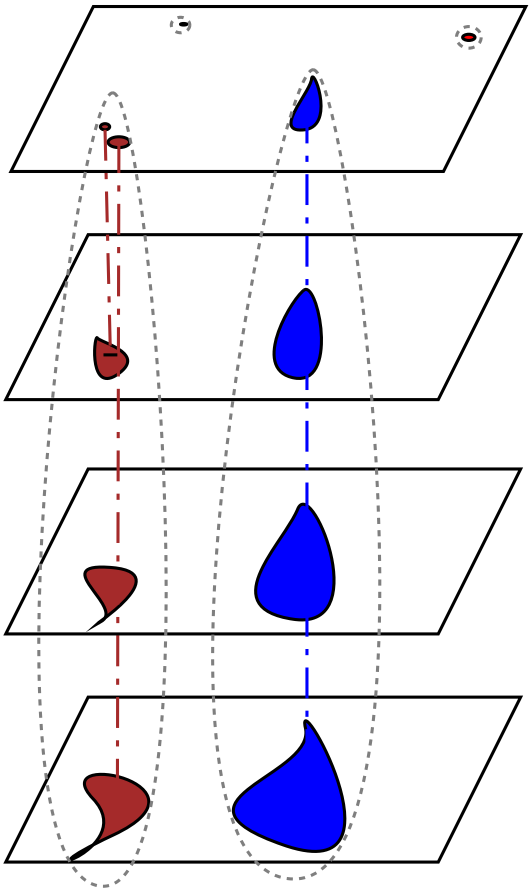

Fig. 5. Illustration of faint source connectivity within the A-trous wavelet scales

2.2.1. *Detection*

The main difficulty in dealing with astronomical faint source detection is the combination of the cosmic ray impacts, and the transient behavior of the detectors and the background level. The capability of detecting the source depends on the number and relevance of available features (the number of raw images of a given target) for the reconstruction of the faint sources. If we consider P_S as the relevant signal and 'P_B, P_N' as the unwanted background (noise), then signal to noise ratio criterion can be used to assess the detection capability of the source target respective to different levels of noise. Figure 4 illustrates the general concept for sources detection and/or estimation. The detection and/or estimation efficiency depends on the signal-to-noise ratio and on the existing amount of information. It depicts two boundaries. There is a lower limit below which source targets are not detectable. There is an upper level above which source targets are detectable and estimable. There is also a region between the two boundaries where the sources can be detectable but not estimable.

2.2.2. *Reconstruction*

As mentioned before, a perfect reconstruction of the faint sources are only possible in the region above the estimation limit. As a conclusion, faint sources could be undetectable in a single temporal signal, but detectable after co-addition of the data for long observation time. Thus, processing techniques can be used to remove the background while distinguishing the sources from the irrelevant information.

Consequently,the major source of errors here is not the detection limit of the instrument, which is quite low, but the possible large number of glitches that create false detection.

2.2.3. *Extended Faint Sources*

Another critical issue on the reconstruction life-cycle is the detection of the extended faint sources. Extended faint source is an object with a dimension that is bigger than that of the image field of view. In this case, the background power is not distinguishable from the source power on a single pointing (Pointing is an observation technique by looking on one target). In this case, it is not feasible to estimate the source target, and different observing modes like raster (i.e. building an image mosaic from single image acquisitions on different pointing targets), or chopping (i.e. switching between two of more pointing targets) have to be used.

3. WAVELET ANALYSIS

The A-trous WVT is an appropriate tool to separate an image into a set of contributions at different scales and frequency bands [4, 16]. Thus, the estimation of a source can be performed by finding the correspondence between given structures in sequence of images at different resolution levels. Figure 5 depicts an illustration of the wavelet analysis of an integration image at different four scales (the finest scale is the top plane). Those scales represent the WVT coefficients space at each resolution level.

This presented approach using the A-trous WVT is efficient for the detection of isotropic structures where the basic elements are elongated shapes with limited directional information. However, astronomical faint sources mainly consist of galactic elements with filamentary structures that are highly anisotropic with smooth contours. For this reason, the CTT transform is introduced in this paper to deal with those smooth 2D singularities.

4. THE CONTRIBUTION OF THIS WORK

This Section presents the limitation problem of separable WVT for the representation of 2D singularities. The CTT

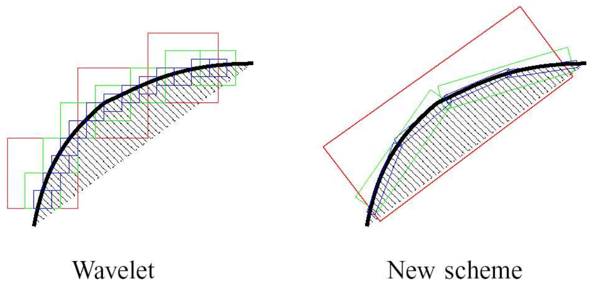

Fig. 6. Illustration of a smooth contour approximation using A. Wavelet and B. Contourlet

approach is proposed to alleviate this problem where an undecimated version of CTT is introduced. The combined approach 'CTT–WVT' is proposed in order to exploit advantages of both approaches in representing isotropic (WVT) and anisotropic structures.

4.1. Wavelets and Contourlets

For efficient non-linear approximation of smooth contours, an appropriate number of directions can be taken versus a limited number of resolutions. Figure 6 illustrates CTT approximation of a smooth boundary versus the classical approximation using WVT [7]. As the resolution becomes finer, WVT needs to use many fine dots to capture the contour. On the other side, CTT explores effectively the smoothness of the contour by making strokes with different elongated shapes and in a variety of directions following the contour. This intuition was first formalized by Candès [6], and then extended by Do and Vetterli in [7].

4.2. The Undecimated A-Trous Contourlet Transform

As the critically-sampled CTT uses a **L**aplacian **P**yramid (LP) and **D**irectional **F**ilter **B**anks (DFB), the decomposition is not translation invariant. Therefore, an undecimated variant at the LP level, i.e the UCTT can be an alternative solution.

In the presented approach, other than in [9], the A-Trous multiresolution transform decomposes the image I:

$$I = \sum_{i=0}^{M-1} \breve{w}_i + r_M \tag{3}$$

into M scales, with coefficients $\breve{w}_i$ and with residuum r_M, thus, replaces the operation of the LP.

A multiresolution transform is a sequence of closed, self-similar subspaces V_n, $n \in Z \; in \; L^2(R)$, which have a hierarchy $[\ldots V_0 \subset V_1 \subset V_2 \subset \ldots]$.

The nested spaces have an intersection that contains the zero function only and a union that is dense in $L(R)$. A scaling function $\Phi \in V_0$ exists with $\Phi\left(x\right) = \sum_{k \in Z} h_k \sqrt{2} \Phi(2x-k)$ for some coefficients $h_k, k \in Z$.

The A-Trous transform can be seen from another point of view as oversampling the original image coefficients by a scaling filter. The kernel of the scaling filter itself is interpolated for every scale, by insertion of $2^k - 1$ zeros (i.e. holes'English'==trous'French'), thus, the number of coefficients are constant in all scales.

The coefficients $\breve{w}_i$ are gained by building the difference between two consecutive scales V_n. Thus, one can argue a different interpretation, in such terms of building an isotropic diffusion time series. The scaling filter in use is the ordinary triangle filter $[\frac{1}{4}\frac{1}{2}\frac{1}{4}]$. The coefficients w_i are then processed by the usual DFB's.

4.3. The Hybrid Multiresolution Approach

The idea developed here is to use the hybrid multiresolution approach UCTT–WVT for a decomposition of a signal into it's set of contributions. The proposed approach [2] consists of four decomposition levels.

- In the first two steps, the undecimated CTT is used. It consists of an undecimated LP and DFB. LP represents a lowpass filtering of the image, and the calculation of the residual image that is the difference between the original image and the lowpass filtered image. Then, the residual image is passed through DFB in order to obtain the UCTT coefficients $h_{1,2}$. Thus, the advantage of UCTT in capturing smooth 2D singularities is exploited in the finest decomposition levels, where anisotropic features may be present.
- In the last two steps, the A-trous WVT is used [13] and the respective coefficients are calculated $h_{3,4}$. Thus, the advantage of A-trous WVT in capturing point-like singularities is exploited in the coarsest decomposition levels, where isotropic features are present.

The multiresolution filtering method consists of measuring the information h (at each multiresolution level) relative to UCTT and WVT coefficients, and of separating this into two parts h_s, and h_n. The expression h_s is called the signal information that corresponds to the power P_S and represents the part of h, which is certainly not contaminated by the noise. The expression h_n is called the noise information that corresponds to the powers $P_B and P_N$ and represents the part of h which may be contaminated by the noise.

The transform coefficients can be decomposed as follows: $h = h_s + h_n$.

Following this notation, the corrected coefficient $w1$ should minimize:

$$J(w1_j) = h_s(w_j - w1_j) + h_n(w1_j) \quad (4)$$

i.e. there is a minimum of information in the residual $(w - w1)$, which can be due to the significant signal, and a minimum of information that could be due to the noise in the solution $w1_j$.

5. CONCLUSIONS

This paper presents a novel approach for efficient faint source extraction from raw images sequence in infrared astronomy. The proposed approach consists of a combination between the undecimated contourlet transform and the A-trous wavelet transform. While contourlets allow the extraction of directional source information (anisotropy), wavelets enable to capture isotropic features.

Thus, the advantages of both transforms are associated in one scheme for effective estimation of different astronomical source structures under dedicated constraints.

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