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Astronomical Image Filtering using Multiscale Wavelet Transforms

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Abstract

Data in the astronomical image processing are characterized by the more presence of noise, In this images noise properties and detector properties are available. The data signal can be a 2 Dimensional image, a 1 Dimensional time- series, a 3D data cube, and variants of these. Signal is what we term the scientifically interesting part of the data. Signal can be compressed, whereas noise by cannot be compressed. Effective separation of signal and noise is of great importance in the astronomical image processing. Noise is the biggest problem in astronomical image processing. If we can estimate noise, through knowledge of instrument properties or through image processing tools, subsequent result obtained would be much better. In fact, major problems would disappear if this were the case image restoration or sharpening could become simpler. Initial focus is estimation of noise in the image using non-orthogonal trous waveletalgorithms.

***Keywords**:-wavelet, trous, astronomical, noise, processing tools*

I INTRODUCTION

Images of astronomical objects are usually taken with electronic detectors such as a CCD (Charge Coupled Device). Similar detectors are found in normal digital cameras. Telescope images are nearly always greyscale, but nevertheless contain some colour information. An astronomical image may be taken through a colour filter. Different detectors and telescopes also usually have different sensitivities to different colors (wavelengths).

Noise is a fundamental problem in image processing and it becomes more important while dealing with very faint astronomical objects. A well known toolfor noise removal is filtering. Conventional one dimensional image filters don't provide proper out for astronomical images, so we have to use non- orthogonal filters based on wavelettransforms.

We have used the wavelet transform, which furnishes a multi-faceted approach for describing and modeling data. There are many 2D wavelet transform algorithms for astronomical image processing such as Chui; Mallat, Burrus. The most widely-used bi- orthogonal wavelet transform is Mallat, This method is based on the principle of reducing the redundancy of the information in the transformed data. Other wavelet transform algorithms exist, such as the Feauveau algorithm which is an orthogonal transform, or the `a trous algorithm which is non-orthogonal and furnishes a redundant dataset. The trous algorithm presents the followingadvantages:

- The computational requirement is reasonable.
- The reconstruction algorithm istrivial.
- The transform is known at each pixel, allowing position detection without any error, and withoutinterpolation.
- We can follow the evolution of the transform from one scale to thenext.
- Invariance under translation is completely verified.
- The transform isisotropic.

Most Astronomical image are isotropic so trous algorithm is best suited for filtering process.

II MULTISCALE TRANSFORMS TROUS ISOTROPIC WAVELET TRANSFORM

The wavelet transform of a signal produces, at each scale j, a set of zero-mean coefficient values {wj}. Using an algorithm trous method this set {wj} has thesame number of pixels as the signal and thus this wavelet transform is a redundant one. using a wavelet defined as the difference between the scaling functions of two successivescales

(12ψ(x2) = φ(x) − φ(x2)),the original signal c0, with a pixel at position k, can be expressed as the sum of all the wavelet scales and the smoothed arraycJ

$$c_{0,k} = c_{J,k} + \sum_{j=1}^{J} w_{j,k}$$

A summary of the `a trous wavelet transform algorithm is as follows.

1. Initialize j to 0, starting with a signal cj,k. Index k ranges over allpixels.
2. Carry out a discrete convolution of the data cj,k using a filter h , yielding cj+1,k. The convolution is an interlaced one, where the filter's pixel values have a gap (growing with level, j) between them of 2j pixels, giving rise to the name `a trous."Mirroring"is used at the data extremes.
3. From this smoothing we obtain the discrete wavelet transform, wj+1,k =cj,k −cj+1,k.
4. If j is less than the number J of resolution levels wanted, then increment j and return to step2.

The set w = {w1,w2, ...,wJ , cJ}, where cJ is a last smooth array, represents the wavelet transform of the data. We denote as W the wavelet transformoperator. If the input data set s has N pixels, then its transform w (w = Ws) has (J + 1)N pixels. The redundancy factor is J + 1 whenever J scales are employed. The discrete filter h is derived from the scaling function φ(x) . In our calculations, φ(x) is a sp line of degree 3, which leads to the filter h = (1/16 , 1/4 , 3/8 , 1/4 , 1/16). A 2D or a 3D
implementation can be based on two 1D sets of convolutions

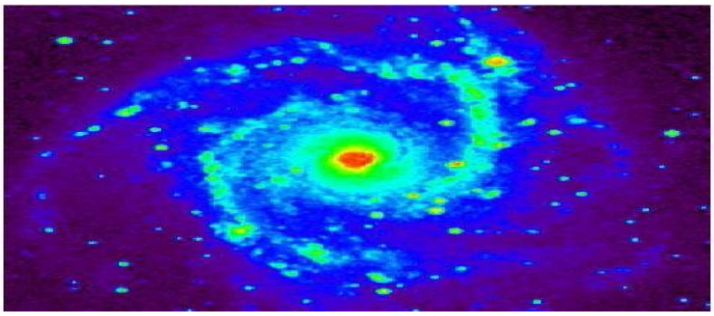

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Figure 1 Galaxy NGC 2997.

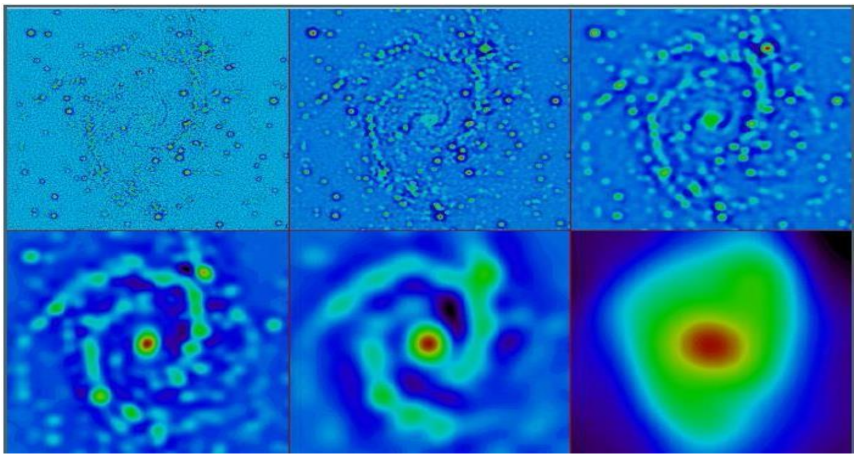

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Figure 2 Wavelet transform of NGC 2997 by the `a trous algorithm

The fig 1 image is given exactly by the sum of these six images.

An important property of the `a trouswavelet transform over other wavelet transforms is shift invariance. Lack of independence to pixel shift is a problem in the case of any pyramidal wavelet transform due to the down-sampling or decimating. The reason is shift-variance is introduced because Nyquist sampling is violated in each ofthe subbands – wavelets are not ideal filters. By not down sampling the problem is avoided. The `a trous algorithm is in fact a fast implementation of a wavelet transform with no downsampling.

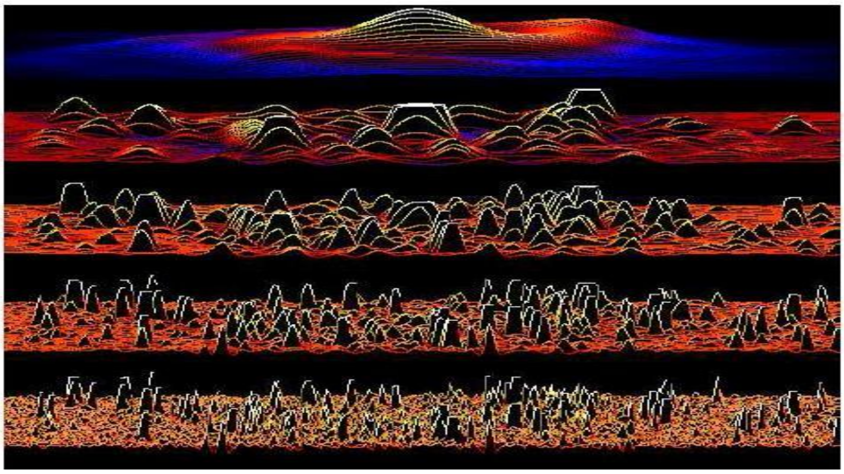

Figure 3 scale as a perspectiveplot.

IIITHE MULTI-RESOLUTION SUPPORT

A multi-resolution support of a data set describes in a logical or Boolean way. It depends on several parameters.

– The inputdata.

– The algorithm used for the multi-resolution decomposition.

– Thenoise.

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– All additional constraints we want the support to satisfy.

Such a support results from the data, the treatment (noise estimation, etc.),and from knowledge on our part of the objects contained in the data (size of objects, linearity, etc.). In the most general case, a priori information is not available to us.First step is calculated using wavelet transform in which we can need to calculate wavelet coefficient. Then the noise induction and removal we have considered Gaussian noise only.

A Noise Modeling

Gaussian noise. If the distribution of wj , l is Gaussian, with zero mean and standard deviation σj , we have the probability density

$$p(w_{j,l}) = \frac{1}{\sqrt{2\pi}\sigma_j} e^{-w_{j,l}^2/2\sigma_j^2}$$

Rejection of hypothesis H0 depends (for a positive coefficient value) on:

$$P = Prob(w_{j,l} > W) = \frac{1}{\sqrt{2\pi}\sigma_j} \int_{w_{j,l}}^{+\infty} e^{-W^2/2\sigma_j^2} dW$$

and if the coefficient value is negative, it depends on

$$P = Prob(w_{j,l} < W) = \frac{1}{\sqrt{2\pi}\sigma_j} \int_{-\infty}^{w_{j,l}} e^{-W^2/2\sigma_j^2} dW$$

Given stationary Gaussian noise, it suffices to compare wj ,l to kσj . Often k is chosen as 3, which corresponds approximately to ϙ = 0.002. If wj, l is Small , it is not significant and could be due to noise. If wj, l is large, it is significant:

if | wj, l | ≥ kσj then wj, l is significant

if | wj, l | <kσj then wj, l is not significant

So we need to estimate, the noise standard deviation at each scale. These standard deviations can be determined analytically, but the calculations can become complicated. so this valves need to be assumed from available data set.

B Automatic Estimation of Gaussian Noise

k-sigma clipping. The Gaussian noise σs can be estimated automatically in a data set s. This estimation is particularly important, because all the noise standard deviations σj in the scales j are derived from σs. Thus an error associated with σs will introduce an error on all σj . Noise is therefore more usefully estimated in the high frequencies, where it dominates thesignal

Table 1 for the first seven resolution levels.

Resolution level j	1	2	3	4	5	6	7
1D	0.700	0.323	0.210	0.141	0.099	0.071	0.054
2D	0.889	0.200	0.086	0.041	0.020	0.010	0.005
3D	0.956	0.120	0.035	0.012	0.004	0.001	0.0005

MAD estimation. The median absolute deviation, MAD, gives an estimation of the noise standard deviation: σm

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= MED(| w1 |)/0.6745, where MED
is the median function. Our noise estimate σsis obtained by:

$$\sigma_s = \frac{\sigma_m}{\sigma_1^e}$$

C Estimation of Gaussian noise from the multi resolution support.

1. Estimate the standard deviation of the noise in s: we have σs^(0).
2. Compute the wavelet transform (`a trous algorithm) of the data s with Jscales, providing the additivedecomposition.
3. Set n to0.
4. Compute the multiresolution support M which is derived from the wavelet coefficients and fromσ(n)
5. Select the pixels which belong to the set S: ifMj,k
= 0 for all j in 1 . . . J
6. For all the selected pixels k, compute the valuessk
− cJ,k and compute the standard deviation σs^(n+1) of these values (we compute the difference between s and cJ in order not to include the background in the noiseestimation).
7. n = n + 1

This method converges in a few iterations, and allows noise estimation to be improved.

IV SIMULATION : IMAGE WITH GAUSSIAN NOISE

A simulated image containing stars and galaxies is shown in (top left). The simulated noisy image, the filtered image and the residual image are respectively shown in top right, bottom left, and bottom right. We can see that there is no structure in the residual image. The filtering was carried out usingthe
Multi resolution support.

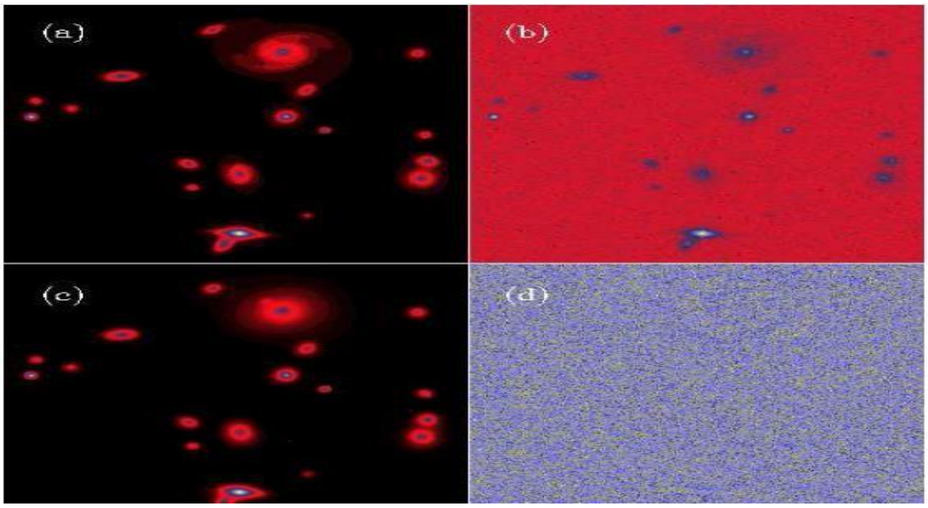

Fig 4 (a) Simulated image, (b) simulated image and Gaussian noise, (c) filtered image, and (d) residual image.

If a realization of the noise can be generated, the detection level can be determined by taking the wavelet transform of the noise map, calculating the histogram of each scale, and deriving the thresholds from the normalized histograms. The normalized histograms give us an estimation of the probability density function of a wavelet coefficient due to noise.

V CHOICE OF MULTISCALETRANSFORM

Shift variance is the property which is different in trous algorithm with other wavelet transform algorithms. The problem is no separate phase shift is available in any wavelet transforms such as Haar, Mallet. this problem is due to down-sampling. In down sampling the Nyquist criteria is not obeyed as filters created by wavelet are not ideal filters .So by using trousalgoritm for wavelet the down sampling problem is avoided**.** The `a trous algorithm is a fast and accurate implementation of a wavelet transform without the need of down sampling.

VI CONCLUSION

The trous transform is isotropic. it provides simplified analysis and proper interpretation of noise in the given images as compared to other non isotropicwavelet transforms .From the results obtained trous algorithm seems appropriate for images containing no favored orientation as in the case of Astronomicalimages.

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